AGENT-BASED MODELING OF COMMERCIAL BUILDING STOCKS FOR ENERGY POLICY AND DEMAND RESPONSE ANALYSIS

A Dissertation
Presented to
The Academic Faculty

by

Fei Zhao

In Partial Fulfillment
of the Requirements for the Degree
Doctor of Philosophy in the
School of Architecture

Georgia Institute of Technology
May 2012

AGENT-BASED MODELING OF COMMERCIAL BUILDING STOCKS FOR ENERGY POLICY AND DEMAND RESPONSE ANALYSIS

Approved by:

Prof. Godfried Augenbroe, Advisor
School of Architecture
Georgia Institute of Technology

Dr. Perry Pei-Ju Yang
School of City & Regional Planning
Georgia Institute of Technology

Dr. William B. Rouse
School of Industrial & Systems Engineering
School of Interactive Computing
Georgia Institute of Technology

Dr. Marilyn A. Brown
School of Public Policy
Georgia Institute of Technology

Dr. Ignacio J. Martinez-Moyano
Decision and Information Sciences Division, *Argonne National Laboratory*
Computation Institute, *The University of Chicago*

Date Approved: March 30, 2012

For my parents who have always supported me

ACKNOWLEDGEMENTS

This dissertation could not be accomplished without the help from many people in my life. I would like to express my deepest appreciation to my parents, who have always loved me, encouraged me, and supported me throughout the ups and downs of my life. I am proud of being their son.

I could never find adequate words to express my gratitude to my advisor Professor Godfried Augenbroe. With his vision into the research frontier, unreserved support, constructive advice, broad knowledge, diligence, and great sense of humor, he has been my role model since my first day of graduate study. I appreciate his profound belief in my work and abilities. I would like to extend my sincere thanks to my committee members for their invaluable advice and suggestions: Dr. Ignacio Martinez-Moyano, Dr. Marilyn Brown, Dr. Perry Yang, and Dr. William Rouse.

I am very grateful to my colleagues in Argonne National Laboratory, where I expended my research area and formulated the applications of this dissertation during my 7-month internship. In this thesis, part of Chapter 6 is a collaborative work with Dr. Ignacio Martinez-Moyano, Dr. Zhi Zhou, Mark Bragen, Kathy Lee Simunich, and Michelle Kehrer. Part of Chapter 7 is a collaborative work with Dr. Zhi Zhou, Vladimir Koritarov, Dr. Jianhui Wang, and John Molburg. In addition, the following people have provided invaluable comments to this research: Guenter Conzelmann, Dr. Diane Graziano, Dr. Ralph Muehleisen, Dr. Michael North, Dr. Cong Liu, Dr. Donald Hanson, and Leahbellah Guzowski.

I would like to extend my sincere thanks to my Georgia Tech professors who were instrumental in providing me state-of-the-art knowledge and excellent demonstration of scholarship. I want to give special appreciation to Dr. Russell Gentry, Dr. Charles Eastman, Dr. Chris Paredis, Dr. Craig Zimring, Dr. Ellen Yi-Luen Do, and Prof. Michael Gamble.

This research has received help from scholars outside the U.S. as well. In Chapter 2, the hourly model was developed based on an example provided by Dr. Dick van Dijk from the Netherlands. In Chapter 3, the way to solve an inverse problem was inspired by Dr. Ruchi Choudhary and Dr. Wei Tian at the University of Cambridge, United Kingdom. I am also deeply indebted to my Tsinghua University mentors in China. They have originally introduced me to the research of building energy efficiency, and provided me many opportunities to grow. Special thanks go to Dr. Yingxin Zhu, Dr. Wenxing Shi, Dr. Xianting Li, and Dr. Bin Zhao.

This thesis would also have not been possible without help from my friends at Georgia Tech. Many thanks to Sanghoon, Yeonsook, Huafen, Jason, Zhengwei, Paola, Atefe, Yuming, Jaeho, Hugo, Andres, Yuna, Qinpeng, Xiaojing, Mindy, Jihyun, Roya, and Yining. We have successfully achieved a lot and enjoyed every single day working together.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF ABBREVIATIONS

ABMS	Agent-Based Modeling and Simulation
ADR	Annual Degradation Ratio
CBECS	Commercial Building Energy Consumption Survey
CDD	Cooling Degree Days
CEN	European Committee for Standardization
DOE	Department of Energy
DR	Demand Response
EUI	Energy Use Intensity
HDD	Heating Degree Days
HVAC	Heating, Ventilation, and Air Conditioning
GHG	Greenhouse gas
GIS	Geographic Information System
LSE	Load Serving Entity
IEA	International Energy Agency
ISO	Independent System Operator
	or International Organization for Standardization
NEMS	National Energy Modeling System
SEER	Seasonal Energy Efficiency Ratio
TMY	Typical Meteorological Year

SUMMARY

Managing a sustainable built environment with a large number of buildings rests on the ability to assess and improve the performance of the building stock[1] over time. Building stock models are cornerstones to the assessment of the combined impact of energy-related building interventions across different spatial and temporal scales. However, such models, particularly those accounting for both physical formulation and social behaviors of the underlying buildings, are still in their infancy.

This research strives to more thoroughly examine how buildings perform aggregately in energy usage by focusing on how to tackled three major technical challenges: (1) quantifying building energy performance in an objective and scalable manner, (2) mapping building stock model space to real-world data space, and (3) quantifying and evaluating energy intervention behaviors of a building stock.

This thesis hypothesizes that a new paradigm of aggregation of large-scale building stocks can lead to (1) an accurate and efficient intervention analysis model and (2) a functionally comprehensive decision support tool for building stock energy intervention analysis. Specifically, this thesis presents three methodologies. To address the first challenge, this thesis develops a normative building physical energy model that can rapidly estimate single building energy performance with respect to its design and operational characteristics. To address the second challenge, the thesis proposes a

[1] A "building stock" in the context of this study refers to a collection of individual buildings located close to one another and behaving similarly in terms of energy consumption.

statistical procedure using regression and Markov chain Monte Carlo (MCMC) sampling techniques that inverse-estimate building parameters based on building stock energy consumption survey data. The outcomes of this statistical procedure validate the approach of using prototypical buildings for two types of intervention analysis: energy retrofit and demand response. These two cases are implemented in an agent-based modeling and simulation (ABMS) framework to tackle the third challenge.

This thesis research contributes to the body of knowledge pertaining to building energy modeling beyond the single building scale. The proposed framework can be used by energy policy makers and utilities for the evaluation of energy retrofit incentives and demand-response program economics.

1 INTRODUCTION

1.1 Background

Global emissions of greenhouse gases from fossil fuel combustion in 2004 were approximately 49 $GtCO_2eq$. Of these emissions, 5.6 $GtCO_2eq$ were emitted in the United States (U.S.). The commercial[2] and residential building sectors were responsible for 18% and 21% of this total, respectively (U.S. EPA, 2008) or a combined 2.2 $GtCO_2eq$. With regard to energy use, commercial and residential buildings in the U.S. account for 39% of primary energy consumption, 71% of electricity use, and 54% of natural gas use (U.S. EIA, 2009a). Energy use for buildings steadily increased from 1985 to 2000 by 17% and is projected to grow annually by 1.7% until 2025 (Ryan & Nicholls, 2004). In fact, the U.S. commercial building sector alone was responsible for more emissions than any single country in Europe was for overall emissions (Colley et al., 2009). Apparently, such emission levels and demand numbers will not allow us to maintain sustainable development given the energy crisis and global warming issues. The building sectors have developed multiple approaches to optimize their energy use, such as improving the energy efficiency of building stock and flattening its demand curves.

[2] A commercial building is defined as a building with more than 50 percent of its floor space used for commercial activities. Commercial buildings include, but are not limited to, offices, enclosed and strip malls, retail stores, educational facilities, hotels, hospitals, clinics, warehouses, restaurants, public assemblies, public safety facilities, and religious facilities.

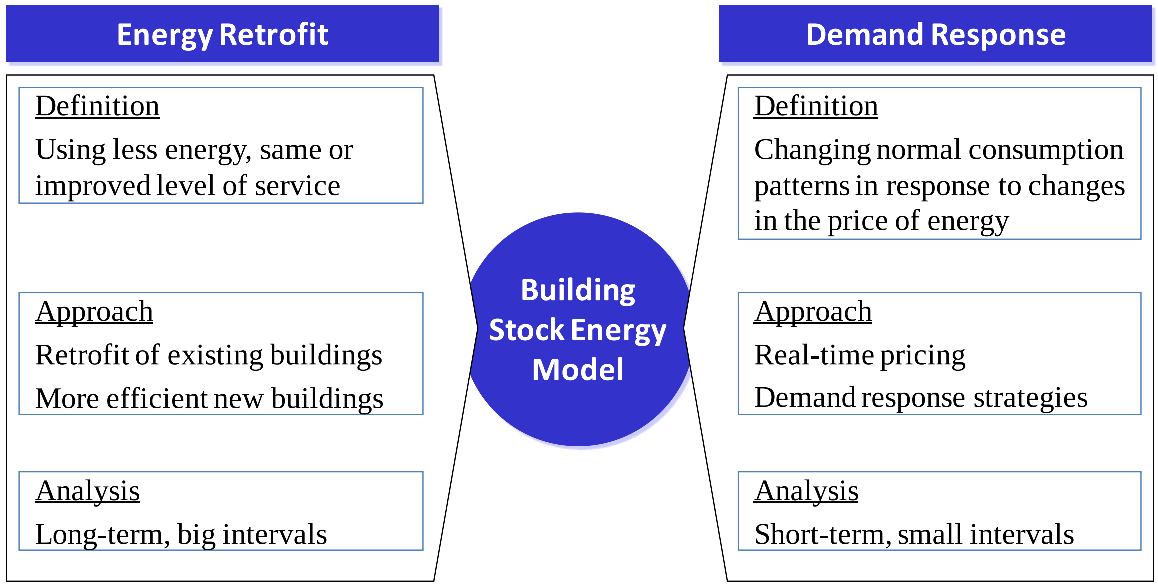


Figure 1 Two energy-related interventions

Achieving higher building energy efficiency demands action by both policymakers and end users. The U.S. government and society, representing policy makers, have developed regulations and technologies for building design and retrofit, especially for commercial buildings. A recent announcement from President Obama states that the U.S. government will provide more tax incentives, more financing opportunities, and stricter regulations to achieve a 20% improvement in building energy efficiency by 2020 (The White House Office of Media Affairs, 2011). In response, the U.S. Department of Energy's (DOE's) Building Technologies Program has set an aggressive commercial building integration and deployment goal to influence the energy performance of 3 billion square feet per year of existing and new commercial floor space with increasing energy-savings targets. These goals must be achieved through a combination of market transformation activities and technology developments. Although the innovation and adoption of new technologies will be important, the development of strategies for deploying existing and emerging technologies at the required speed and scale has been challenging. To verify if an energy efficiency plan is achievable in the long term and to evaluate if an energy reduction goal is met at the given time, one must be able to estimate the energy performance of an entire building stock without metering or auditing every individual building in the stock. At the same time, from the perspective of the end user, building owners have diverse attitudes towards policies and incentives and acceptance levels of adopting energy efficient technologies for their buildings. Hence, to serve the need for policies that address energy efficiency, a building stock energy model must be capable of reflecting the current condition and projecting future interventions with respect to decision making aspects from policymakers and building owners.

Flattening the demand curves of building stock requires input from two sources: utility companies and consumers. Utility demand response (DR) programs, administered by the utilities, give consumers the power to manage their energy use in response to supply conditions. A recent study conducted by the Federal Energy Regulatory Commission (FERC) estimated that if price-responsive programs were universally added to the mix of existing load demand programs in the United States, a reduction of 20% in peak demand could be achieved by the year 2019 (Federal Energy Regulatory Commission, 2008). To enable demand response, electricity markets in a number of regions such as the Pennsylvania-New Jersey-Maryland Interconnection (Mansur, 2003) have been restructured away from operating as centralized markets to operating as competitive markets. This evolution has dramatically changed how power systems operate. In traditional power systems, supply from committed generation units is scheduled to follow any change(s) in load demand. During a peak load period, the load can be very high, so more generators have to be committed. As a result of this usage pattern, operators must increase their investment in additional generators that may be committed for only a few hours a year. To reduce the need for investment in more generation capacity, DR can reduce peak loads or adjust the demand in peak times. Moreover, in regions with high rates of penetration of renewable energy sources, DR can trigger changes in demand that follow changes in supply. To facilitate electricity grid planning, regional transmission organizations and policymakers must be able to evaluate the load and market consequences from various levels of DR participation of consumers. In addition, from the perspective of the consumer, power distribution companies also need to be aware of the energy and monetary savings from the application of DR strategies. Thus, to answer the need for energy management in the smart grid, the building stock energy model must estimate the energy and monetary consequences of different demand response strategies of building owners.

1.2 A Review on Building Stock Energy Models

Simulation models are expected to play an important role in the development of future urban sustainability because they enable us to predict and recreate visible phenomena that are not normally observable (Tweed, 1998). To estimate the energy consumption and the CO_2 emissions of building stocks over time, researchers have developed various modeling methods. Groups in Canada (Swan & Ugursal, 2009), the United Kingdom (Kavgic et al., 2010), and the United States (Martinez-Moyano, Mahalik, Graziano, & Conzelmann, 2010) reviewed some of the existing building stock models. Based on the techniques for modeling energy consumption, these methods can be classified into two categories: “top-down” and “bottom-up,” represented by the building sector as a whole and the hierarchal position of data inputs, respectively. In the literature, we found two definitions of these two approaches, which explain in different languages but the similar concept:

Swan & Ugursal (2009): “The top-down approach treats the residential sector [or building stock] as an energy sink and is not concerned with individual end-uses. It utilizes historic aggregate energy values and regresses the energy consumption of the housing [or building] stock as a function of top-level variables such as macroeconomic indicators (e.g., gross domestic product, unemployment, and inflation), energy price, and general climate. The bottom-up approach extrapolates the estimated energy consumption of a representative set of individual houses [or buildings] to regional and national levels.”

Kavgic, et al. (2010): “Top-down models utilize estimates of total building sector energy consumption and other pertinent variables to *attribute* energy consumption to characteristics of the entire building stock. In contrast, bottom-up models calculate the energy consumption of individual or groups of prototypical buildings and then extrapolate the results to *represent* the region or the nation.”

This study reviews published cases of the abovementioned approaches and determines the room of improvement in this research and development field. Table 1 presents a comparison of different top-down and bottom-up models reviewed by this study.

Table 1 A summary of existing building-stock energy models

Model Name	Approach	Bldg. Type	Developer	Year Est.	Core Calculation Algorithm	Spatial Resolution	Temporal Resolution
World Energy Model	Top-down	Various	IEA	1994	Constant annual increase rates	National	Annual
ACEEE meta-analysis of 11 studies	Top-down	Various	US: ACEEE	2004	Comparison of other models in the literature	National, regional, and urban	Annual
IPCC "economic mitigation potentials"	Top-down	Various	IPCC	2007	Unknown	National	Annual
NEMS	Bottom-up, statistical	Various	US: EIA	1994	Market equilibrium of end-use prices and quantities	National	Annual
McKinsey's energy study	Bottom-up, statistical	Various	McKinsey & Company	2007	Data based on NEMS	National	Annual
"The BREDEM Family": BREHOMES, Johnson, UKDCM, DECarb, CDEM	Bottom-up, physical	R	UK: Building Research Establishment (BRE) and various research institutes	1990s-2000s	BREDEM-12, BREDEM-8	Regional	Monthly
CREEM	Bottom-up, physical	R	Canada: Canadian Residential Energy End-use Data and Analysis Centre (CREEDAC)	1998	HOT200 Batch v7.14	Regional	Annual
Regional engineering model	Bottom-up, physical	R	Finland: University of Joensuu	1999	unknown	Regional	Annual
VerbCO_2M	Bottom-up, physical	R	Belgium: Laboratory for Buildings Physics	2001	VerbCO_2M	Regional	Annual
NREL's US commercial building sector model	Bottom-up, physical	C	US: National Renewable Energy Laboratory (NREL)	2007	EnergyPlus	National	Hourly/Annual
LBNL US commercial building sector model	Bottom-up, physical	C	US: Lawrence Berkeley National Laboratory (LBNL)	2008	Simple formula based on building floor area	National	Annual
GridLab-D	Bottom-up, physical	R	Pacific Northwest National Laboratory (PNNL)	2009	Equivalent Thermal Parameters (ETP)	Individual buildings	Hourly
Osaka Univ.'s model	Bottom-up, physical	C	Japan: Osaka University	2009	unknown	Regional	Monthly
Hydro-Quebec	Bottom-up, physical	C	Canada: Hydro-Quebec	2009	EnergyPlus	Regional	Hourly/Annual

Several top-down models are capable of predicting the "macroeconomic" performance of building stocks and the impact of various "what-if" scenarios over time. Prominent examples of such approaches include the World Energy Model used by the International Energy Agency (IEA) to model reference scenarios for the World Energy Outlook (IEA, 2008), the model supporting IPCC "economic mitigation potentials" (IPCC, 2007), and the efficiency analysis and the meta-analysis conducted by both the American Council for an Energy Efficient Economy (Nadel, Shipley, & Elliott, 2004) and the alliance to Save Energy in support of the President's Climate Action Plan. Building energy components in these top-down models are typically modeled as per-area properties of energy items. The energy performance of a building is then calculated as the weighted sum of the building energy items and the deployment of future energy efficiency technologies. These top-down, macroeconomic models are typically based on statistical relationships amongst economic conditions, energy use, and technology adoption derived from empirical data collected over time. Their projections generally assume that such relationships will be preserved into the future. Since historical data are directly used to derive such relationships, macroeconomic models are more accurate than physical models at reflecting the energy performance of the building stock. However, statistical models are data demanding and less adaptable, so they cannot predict results for scenarios with inadequate or no prior knowledge. Therefore, top-down building stock models are weak at analyzing interventions in building design and operational specifications (e.g., a comparison of the various retrofit options is difficult if they are new to the model).

Compared to top-down models, bottom-up models are more prevalent in the literature. The bottom-up approach consists of two distinct methodologies: the statistical technique and the physical technique. Bottom-up statistical techniques for determining energy end-uses including behavior based on energy bills and simple survey. The most widely used example is the building module of the National Energy Modeling System (NEMS) used by the United States Energy Information Agency (EIA) (EIA, 2009). NEMS is a modulized, long-term energy model the U.S. energy economy. The overall model operates each simulated year (typically 25 years) by iteratively executing each of the modules in sequence until general market equilibrium of end-use prices and quantities is achieved across all modules. the Another example, McKinsey cost-abatement-curve analysis, uses NEMS as a data source to evaluate GHG emission reduction potentials of different technologies (Enkvist, Nauclér, & Rosander, 2007; Granade et al., 2009). All examples of the bottom-up statistical technique are developed for the spatial scale of a nation or the entire world.

Bottom-up physical techniques, constructed according to building physics and detailed characteristics, enable analysis of impacts of new (or alternative) technologies. Every bottom-up engineering building stock model represents only one building type: "residential" (domestic, home, or dwelling) or "commercial" (non-domestic or non-residential). Most research efforts have focused on residential buildings. In the United Kingdom, the Building Research Establishment (BRE) developed the BREDEM model as a single building energy model (Anderson et al., 2001; Henderson & Shorrock, 1986). BREDEM uses a combination of physical and empirical relationships to calculate the energy consumption of a single house. Several prominent UK national housing stock models that have used BREDEM as their engine include the BREHOMES model, developed by BRE (Shorrock & Dunster, 1997); the model developed by Johnson in Leeds University (Johnson, Lowe, & Bell, 2005); the UK Domestic Carbon Model (UKDCM), developed by Oxford University (Boardman, 2007); the DECarb model, developed by Natarajan & Levermore (2007); the Hydro-Quebec interface developed by the Hydro-Quebec Research Institute (Sansregret & Millette, 2009); and the Community Domestic Energy Model (CDEM), proposed by Firth, Lomas, & Wright (2010). In addition to BREDEM-based UK models, other groups have also developed residential building stock models with distinct characteristics, including models in Canada (Farahbakhsh, Ugursal, & Fung, 1998), Finland (Snakin, 2000), and Belgium (Hens, Verbeeck, & Verdonck, 2001). All of these bottom-up residential building stock models have calculation engines customized for residential buildings in specific locations. Moreover, each building stock model also contains a set of prototypical building designs (also called "archetypes" in the literature) to represent typical buildings in a country. These location-related properties cannot be directly adopted or applied to any other country.

Bottom-up physical models have not been applied to commercial buildings as much as they have to residential buildings. Several previous projects have created prototypical building energy models in the United States. The most referenced is from the Lawrence Berkeley National Laboratory (LBNL), which developed a series of prototypical buildings over several years. Huang, Akbari, Rainer, & Ritshard (1991) and Huang & Franconi (1999) present extensive summaries of work in this area; Huang, Roberson, & Roberson (2005) present an analysis of the 1999 building data. Three recent efforts at developing prototypical energy models of buildings include a set of standardized energy simulation models for commercial buildings from the University of Massachusetts (Stocki, Curcija, & Bhandari, 2007), a residential building benchmark model from the DOE Building America Program (Hendron, 2008), and an assessment of the entire commercial building sector by the National Renewable Energy Laboratory (NREL) (Griffith et al., 2007, 2008). These commercial reference building models are detail-driven and comprehensive. However, they have been developed and maintained as Energy Plus files. In a large-scale study, a large number of Energy Plus models have to be solved with considerable computing time. Thus, this is a drawback of bottom-up physical models.

1.3 Motivation

Evaluating the results of the energy and emission reduction approaches necessitates methodologies and tools that support the analysis of energy use in the building stock over time. Such tools must reflect the physical relationships between various causes (e.g., building design and operational characteristics) and effects (e.g., energy use and CO_2 emissions over time). They should also be computationally affordable for a variety of users asking diverse questions.

Among the current building stock modeling methods, a large number of bottom-up models that are technical or statistical typically require an enormous number of dynamic, computationally intensive energy simulations (Griffith et al., 2007, 2008; Yohei Yamaguchi, Shimod, & Mizuno, 2007). Some other top-down models that are technical or econometric yield higher efficiency but lack the comprehensiveness and transparency of studying interventions in building design and operational parameters.

Among the current power grid simulation methods, commercial buildings, as major consumers, are typically modeled as predefined, aggregated, and fixed-load profiles or demand curves on the basis of historical regional electricity consumption data in the existing literature (Dam, Houwing, & Bouwmans, 2008; Exarchakos, Leach, & Exarchakos, 2009; Vytelingum, Voice, Ramchurn, Rogers, & Jennings, 2010). In reality, however, buildings of different types are typically distinctive (i.e., they have different energy consumption patterns that are determined by climate, condition, and building design and operation) and autonomous (i.e., they are responsive to electricity prices in different ways). Thus, the analysis of the power system calls for a method of modeling the interaction between the building stock and the power grid. This method should be able to estimate large-scale energy use intensities for the building stock without expert-driven, heavy-duty, dynamic energy simulations for each building within the stock—dynamic simulations that are not applicable when the design details of the buildings in the stock are inadequate. Therefore, it is important that we develop a method and a tool that excel in both computational efficiency and decision analysis capability for building stock modeling.

What we learned from the literature review is that to effectively estimate and project the potential of energy savings and GHG emission reduction of new (or alternative) technologies, bottom-up physical building stock models are the best choice. However, these models are short of computational efficiency and capability of studying interventions in different temporal and spatial scales. To develop models that meet current desire, a number of considerations are important in shaping the methodology and its implementation in this study. These considerations, some of which are adapted from Colley, et al. (2009), are shown as follows.

1) **The ability of modeling different scenarios**: The model should be able to answer a variety of "what if" questions, for example, "What would be the consequences if buildings are encouraged to install double-glazing, low-e windows?"
2) **The desire of transparency and user interactivity**: Users of the model should be able to easily relate building design parameters to policy or utility figures. They should also be able to specify the characteristics of different roles of participants in the commercial building sector.
3) **Support for the current condition and long-term interventions**: The model should be able to estimate the current condition of building energy performance across the entire building stock. Meanwhile, it should also be able to estimate long-term energy performance with respect to the performance degradation of buildings, the retrofit decision making of owners, and regulation changes by policy makers.
4) **The need for fast run times**: The model should be capable of supporting the modeling of different scenarios and long-term interventions. Modeling large-scale commercial building stocks and thousands of representative buildings in a dynamic simulation, let alone modeling every single building in the stock, consumes too much time. Therefore, a better way of aggregating representative buildings and estimating energy performance of these buildings should be developed.

5) **The capability of modeling in different temporal durations and resolutions**: The model should be able to be applied to both long-term stock retrofit and short-term DR potential analysis.

1.4 Research Questions and Hypotheses

This research develops an energy modeling approach that estimates urban-, regional-, and national-scale building energy consumption for large-scale building stock without modeling every building in the stock. This approach should facilitate decision making for energy efficiency policy and energy management.

This thesis hypothesizes that a new paradigm of aggregation of large-scale building stocks can lead to (1) an accurate and efficient intervention analysis model and (2) a functionally comprehensive decision support tool for building stock energy intervention analysis.

To test the first major hypothesis, this thesis has broken it down into five measurable sub-hypotheses and created a set of mathematical experiments to test them. These sub-hypotheses are:

- *Hypothesis 2A*: Using exactly the same inputs, the normative building energy model is capable of predicting similar results compared to the dynamic simulation model, in this case, Energy Plus.
- *Hypothesis 3A*: The probability distribution function (PDF) of commercial building energy consumption in a specific city can be extrapolated by a statistical transformation of the energy consumption PDF of a larger area including that city based on climate.
- *Hypothesis 3B*: Given feasible ranges of building design parameters, a set of inputs and the output (primary energy use intensity, EUI) of the normative building energy model can be expressed as a linear regression model.

- *Hypothesis 3C*: Given (1) the distribution of building primary EUI in a city and (2) a linear estimation of a building energy model, one could solve a linear inverse problem to generate distributions of the building energy model input variables, which can replicate the building stock primary EUI distribution.
- *Hypothesis 4A*: Estimating energy efficiency interventions at the whole building stock level does not require massive simulation of individual buildings in the stock. Instead, prototypical buildings could sufficiently predict the intervention effects such as performance degradation, energy retrofit, and demand response.

To test the second major hypothesis, this thesis implements two simulation platforms for large-scale retrofit modeling for energy policy analysis, and price-based demand response analysis. The proposed building stock model has been demonstrated in several test cases in this thesis and shown to be capable for the target purposes.

Technically, these hypotheses will be investigated through the creation of a large-scale building stock analysis tool and the testing of this tool in two aspects:

1) Determining the feasibility of the normative building energy model for large-scale building energy analysis by comparing simulation results estimated by the proposed method and those estimated by massive modeling.
2) Demonstrating the capability of the proposed framework to model the composition and dynamics of the building stocks by developing simulation algorithms of building stock transformations (retrofit and degradation) and reactions (demand response).

1.5 Who Will Benefit from This Thesis

This thesis research contributes to the body of knowledge pertaining to building energy modeling beyond the single building scale. The regression analysis and inverse problem solving techniques can be used by scholars and engineers to derive more information from city-wide energy consumption data. Besides, the prototype-based building stock model can be used by city planners, district-level retrofit practitioners, utilities, and energy efficiency policy makers to evaluate design alternatives, retrofit programs, and demand response economics.

1.6 Thesis Outline

This thesis is organized following the order of building stock model development. Chapter 2 first introduces and validates a normative single building energy model that can be used as the engine of the building stock model. Chapter 3 then proposes a method to replicate building stock model parameters for massive modeling of a collection of buildings. In addition, Chapter 4 proposes a more scalable and efficient building stock model based on prototypes, and validates it with the statistical model proposed in Chapter 3 and massive models. Joining this prototype-based model, Chapter 5 introduces the agent-based modeling and simulation technique that is further used in a large-scale retrofit analysis framework in Chapter 6, and a large-scale demand response analysis framework in Chapter 7. Chapter 8 concludes the thesis with major findings and conclusions.

2 NORMATIVE BUILDING ENERGY MODELING

2.1 Introduction

As defined in Chapter 0, the objective of this thesis is to develop a bottom-up building stock energy model that quantifies the physical and social behaviors involved in a built environment. Various whole building energy models that model the physical built environment, including statistical models, normative models, nodal network models, and fully dynamic simulation models, have been developed. Among those with different levels of fidelity, normative building energy models have been found to have an adequate level of detail and scalability to support large-scale retrofit decision analysis (Heo, 2011). Thus, this thesis follows the principles of normative models and implements a version for the retrofit and demand response analysis.

This chapter begins by briefly introducing the fundamental components of this normative building energy model and its implementation in this research, EPSCT (Lee, Zhao, & Augenbroe, 2011), in Section 2.2. Section 2.3 introduces input and output variables of this model. Section 2.4 then validates the implementation of the model by comparing it to other whole building energy models via some test cases. Section 0 concludes this chapter.

2.2 Normative Building Energy Model

This thesis develops a normative building energy model ("normative model" in abbreviation) for commercial buildings with respect to their diversity of program, materiality, HVAC, equipment, and weather data. The model will be able to quickly estimate building energy consumption with acceptable confidence in different output aspects and time step sizes.

Several models and tools that evaluate the energy use and the conditions of indoor environments in commercial buildings have been developed. They range from simplified, first-order-physics procedures useful for hand calculations to dynamic simulation models that use detailed numerical calculations of heat, air, and moisture transfer by sophisticated systems that control temperature, daylight, and so forth. To maintain a high level of transparency, reproducibility, and robustness, the quasi-steady state calculation procedures often use few input data and a limited set of equations. The major benefits of the normative model are that it (1) reduces input parameters as much as possible, (2) makes modifications to the input parameters easily by directly using the building design and operational parameters to be implemented, and (3) maintains an adequate level of accuracy, particularly for air-conditioned buildings in which the thermal dynamic of the indoor environment has a high impact.

ISO 13790, Energy Performance of Buildings—Calculation of Energy Use for Space Heating and Cooling (ISO, 2008), specifies such a simplified building energy calculation approach developed by the European Committee for Standardization (CEN) in its Energy Performance of Buildings Directive (EPBD) Program as well as its original developers (Van Dijk & Spiekman, 2003; Van Dijk, Spiekman, & De Wilde, 2005). This standard provides different types of calculation methods, including a seasonal or monthly method, a simple hourly method, and a detailed simulation method. Lee, Zhao, and Augenbroe (2011) from the Georgia Institute of Technology have developed a normative model referred to as the Energy Performance Standard Calculation Toolkit (EPSCT), based on ISO 13790 and several other relevant standards. The normative model used in this thesis is based on EPSCT and ISO 13790.

2.2.1 The Monthly Method

The monthly method of building energy calculation is based on a monthly balance of heat gains and losses determined in steady state conditions. It takes into account dynamic effects by introducing an internal temperature adjustment for heating and cooling intermittency and a utilization factor for the gain-loss mismatch. The basic formulations of the model are

$$Q_{H,nd} = Q_{H,ht} - \eta_{H,gn} Q_{H,gn} \qquad (2\text{-}1)$$

for the building thermal need of continuous space heating, and

$$Q_{C,nd} = Q_{C,gn} - \eta_{C,ls} Q_{C,ht} \qquad (2\text{-}2)$$

for the building thermal need of continuous space cooling, where

$Q_{H,ht}$ is the total heat transfer for the heating mode;

$Q_{H,gn}$ is the total heat gains for the heating mode;

$Q_{C,ht}$ is the total heat transfer for the cooling mode;

$Q_{C,gn}$ is the total heat gains for the cooling mode;

$\eta_{H,gn}$ is the dimensionless utilization factor for heat gains in the heating mode; and

$\eta_{C,ls}$ is the dimensionless utilization factor for heat losses in the cooling mode.

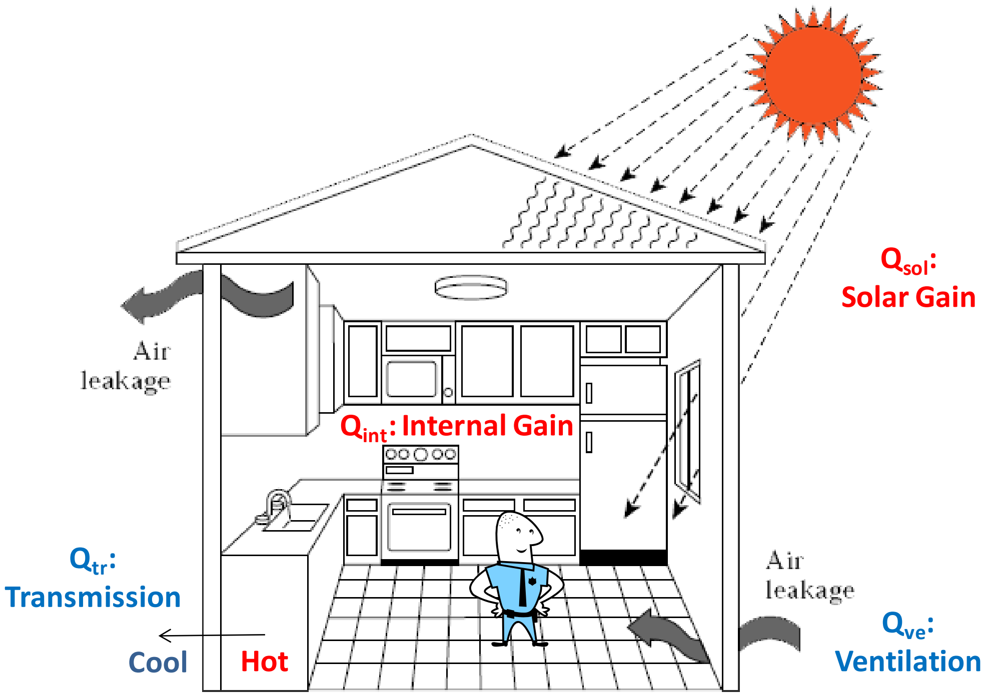


Figure 2 Schematic of heat transfer and heat gains of a building

For each calculation zone in each calculation time step t, the total heat transfer (Q_{ht}) is calculated by summing the heat transfer through transmission (Q_{tr}) and ventilation (Q_{ve}):

$$Q_{ht} = Q_{tr} + Q_{ve} \tag{2-3}$$

$$Q_{tr} = \sum_i (U_i A_i)\,(\theta_{air} - \theta_{ext})t \tag{2-4}$$

$$Q_{ve} = \dot{V}_{air}\rho_{air}c_{air}(\theta_{air} - \theta_{ext})t \tag{2-5}$$

where for each building envelop element i,

U_i	is the heat conduction coefficient;
A_i	is the area of surface element i;
$\theta_{air}, \theta_{ext}$	are the internal set-point and the external air temperature;
$\dot{V}_{air}$	is the air exchange volume rate in each time step; and
ρ_{air}, c_{air}	are the density and specific heat capacity of air.

The total heat gains (Q_{gn}) of the building for a given calculation step can be calculated by summing the heat gains from internal production (Q_{prod}) and solar radiation (Q_{sol}):

$$Q_{gn} = Q_{prod} + Q_{sol} \tag{2-6}$$

$$Q_{prod} = A_{flr}(f_{occ}\varphi_{occ} + f_{app}\varphi_{app} + f_{lit}\varphi_{lit})t \tag{2-7}$$

$$Q_{sol} = \sum_i (f_{sh,i} I_i A_{sol,i} - F_{r,i}\,\varphi_{r,i})t \tag{2-8}$$

where for each building envelop element i,

A_{flr}	is the conditioned floor area;
f_{occ}, f_{app}, f_{lit}	fractions of heat gains from occupants, appliances, and lighting;
φ_{occ}, φ_{occ}, φ_{occ}	heat production intensities of occupancy, appliances, and lighting;
$f_{sh,i}$	the shading reduction factor;
I_i	the solar irradiance, the mean solar radiation received over one time step, per square meter of collecting area of surface i;
$A_{sol,i}$	the effective collecting area of surface i given its orientation, tilt angle, heat conduction, and convection coefficients (for opaque) and solar heat gain coefficient (for glazing);
$F_{r,i}$	the form factor between the building element and the sky; and
$\varphi_{r,i}$	the long wave radiation flow rate from the element to the sky.

The utilization factors represent the portion of gains (during the heating season) or losses (during the cooling season) that contribute to the reduction in the heating demand (during the heating season) or in the cooling demand (during the cooling season). The non-utilized part of the gains (in winter) or the losses (in summer) depends on the dynamic mismatch between the gains and the losses, which may cause heating above the heating temperature set point in the winter or cooling below the cooling temperature set point (e.g., during summer nights).

In order to calculate heating and cooling energy consumption, this monthly energy model uses the overall efficiencies of the building energy generation and distribution systems. Models compute total building distribution loss from normatively defined factors for pipe and duct losses and energy waste due to simultaneous heating and cooling. Models define heating/cooling generation efficiencies as annual system efficiencies that take into account their efficiency under dynamic conditions throughout the year. With the use of overall efficiencies, this method computes energy consumptions for heating and cooling from thermal needs. In order to calculate other sources of building energy consumption (e.g., lighting, equipment, fans, pumps, and domestic hot water), a set of EPBD standards (Hogeling & Van Dijk, 2008) describes the empirical coefficients for estimating the performance of building systems, the consumption of delivered and primary energy, and the emissions of greenhouse gases. This study will test and validate the monthly method together with the hourly method against EnergyPlus, a dynamic building energy simulation software developed and maintained by the U.S. Department of Energy (DOE, 2010).

2.2.2 The Hourly Method

Besides the monthly method, ISO 13790 also introduces a simple hourly method based on an equivalent resistance-capacitance (R-C) network. Heat transfer by ventilation, infiltration, solar radiation, and internal heat gains are considered flows into various building component nodes, so the hourly indoor air temperature as well as heating and cooling loads of a building can be calculated. In this model, the input parameters include building geometry (e.g., floor area, elevation, and window-wall ratios); materiality (e.g., U-values, light transmission, and the absorption factors of enclosures); heating, ventilation, and air conditioning (HVAC) (e.g., the schedule, efficiencies, and set-point temperatures); and lighting and equipment (e.g., intensity and the schedule).

Typical meteorological year (TMY) hourly weather data are also used. Then, the heating and/or cooling needs are found by calculating, for each hour, the heating or cooling power (φHC,nd) that must be supplied to or extracted from the indoor air node (θair) to maintain a certain set-point indoor air temperature.

Heat transfer by ventilation (Hve) is connected to the supply air temperature (θsup) and the interior temperature (θint). Heat transfer by transmission is split into a window part (Htr,w) and a non-window part (Htr,em and Htr,ms); only the non-window part is connected by a single thermal capacity (Cm), representing the building thermal mass.

Heat gains from internal and solar sources are split into three parts (φair, φs, and φm) and applied to the nodes of indoor air (θair), the internal environment (θs), and the thermal mass (θm), respectively. Figure 3 depicts these elements of the simple hourly method.

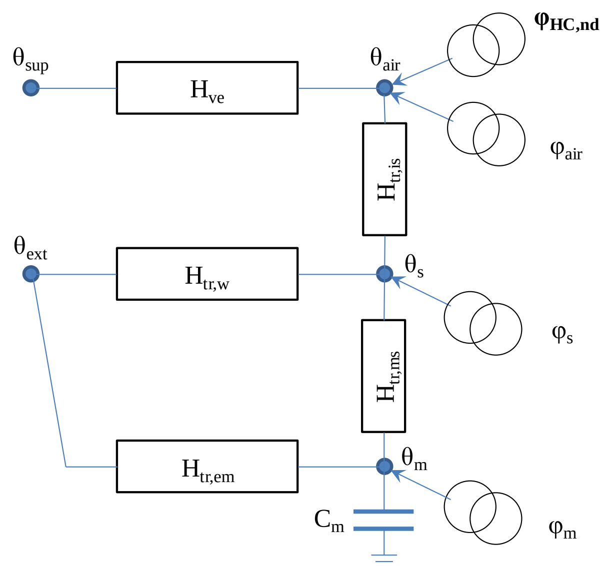


Figure 3 Thermal R-C model of the simple hourly method [based on (ISO, 2008)]

2.3 Output Performance Indicators

The normative requires several input parameters to compute output variables. Figure 4 illustrates all the desired inputs and outputs of the normative model.

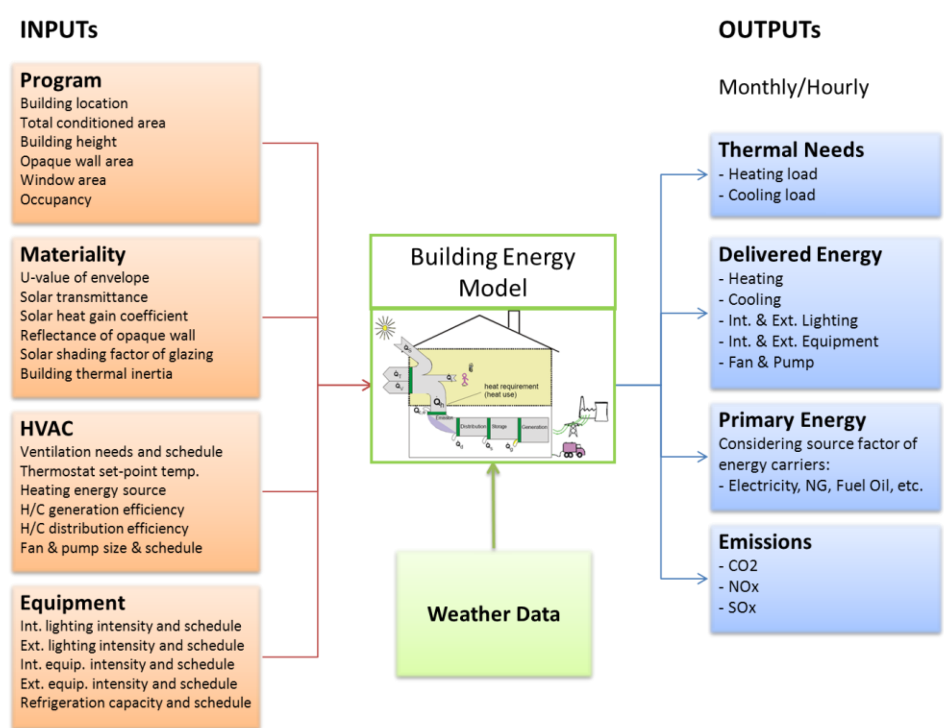


Figure 4 Input and output structures of the desired normative building energy model

The input parameters are simpler that those required by typical dynamic building simulation models. Here they are categorized into four groups: program, materiality, HVAC, and equipment. Using the TMY3 weather data, the model computes outputs, categorized by different levels of energy, as shown in Figure 4.

2.4 Validation of the Normative Model

Comparative validation of the simple hourly method has been performed against detailed dynamic simulations at the level of thermal needs (Millet, 2007; Nielsen, 2005). In addition to the existing work in literature, this section compares the delivered energy calculated by Energy Plus and the normative model (both monthly and hourly). The underlying hypothesis to be tested in this validation process is as follows.

Hypothesis 2A: Using exactly the same inputs, the normative building energy model provides similar results compared to dynamic simulation models, in this case, Energy Plus.

2.4.1 Validation of the Monthly Method

In this thesis, the objective of the monthly method is to rapidly estimate whole building energy performance on an annual basis. Thus, this test compares the annual delivered energy use intensity (EUI, in kWh/m^2, year) of a set of buildings calculated by the normative model and Energy Plus. This test includes 77 selected buildings, including:

- 19 on-campus buildings at Georgia Tech, Atlanta, Georgia, USA
- 10 newly-designed office buildings in Doha, Qatar
- 48 DOE reference buildings (small, medium, and large offices in three vintages) located in 16 U.S. climate zones

The calculation results are plotted in Figure 5. Results of the comparison indicate that most of the energy result points fall between the dotted lines, indicating that the relative deviation between the two results is less than 20%. This finding is especially true for the results of DOE reference buildings that will be used as prototypes in the building stock model proposed in Chapter 4.

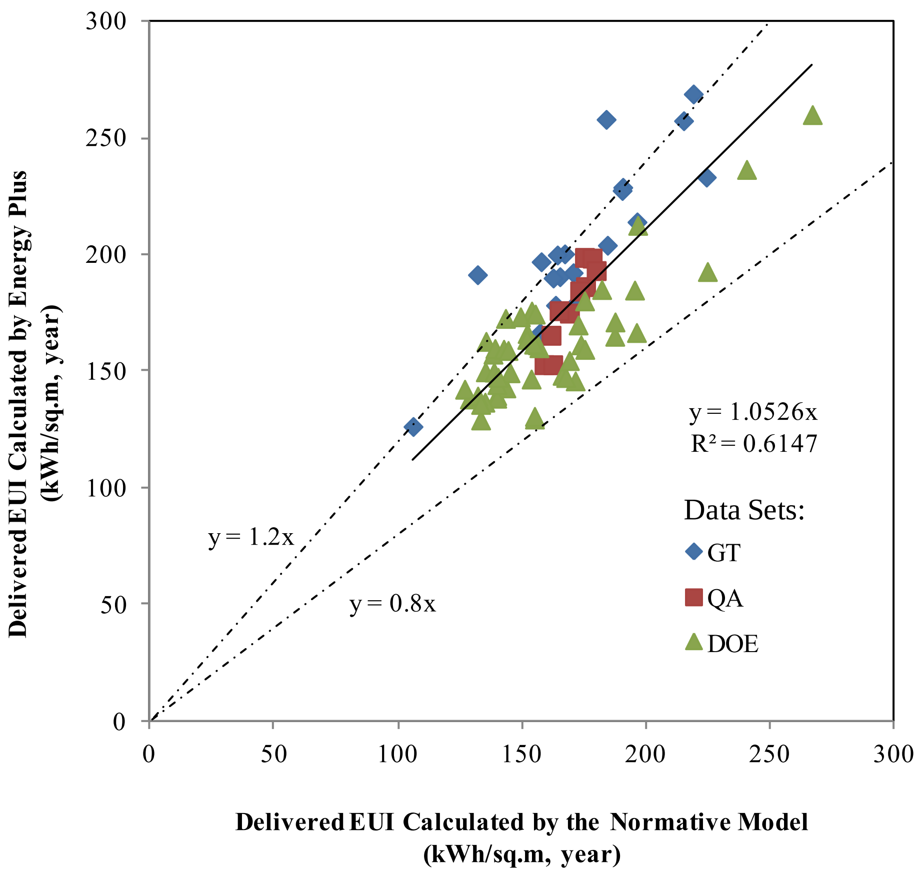


Figure 5 Delivered EUI of 77 buildings modeled by Energy Plus and the monthly normative model

A linear regression of these 77 data points shows that the results of Energy Plus is on average 5.2% higher than those of the normative model, with an R^2 value of 0.61, an acceptable deviation for building energy modeling, given the much higher uncertainties in the model parameters and measurement errors.

2.4.2 Validation of the Hourly Method

In this thesis, the objective of the hourly model is to estimate the dynamics of building electricity consumption so that demand response can be modeled. This test takes a large prototypical office building as an example to compare the hourly energy outcomes modeled by Energy Plus and the normative model. The reference office illustrated in Figure 6 represents an existing office in a building built after 1980 in Chicago, Illinois. The total conditioned floor area of this 12-story building is 46,320 m^2. Its primary heating source is natural gas.

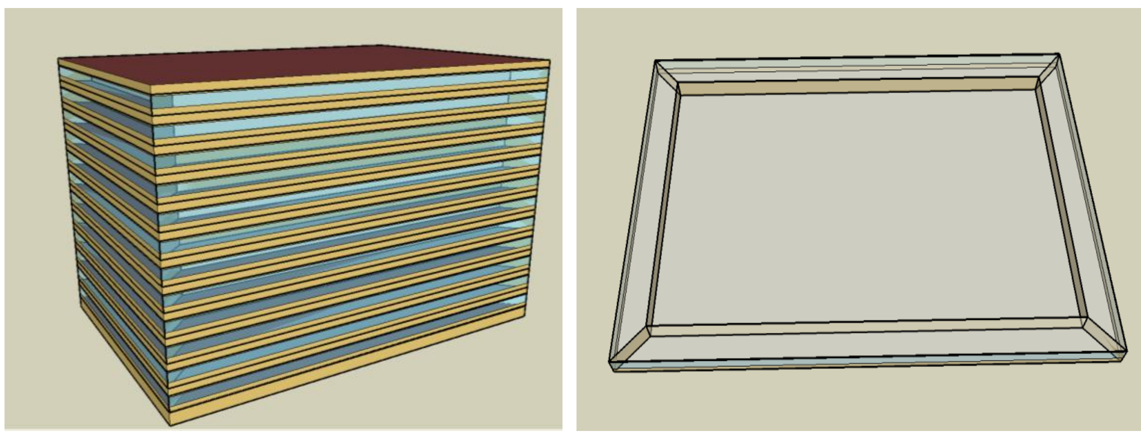


Figure 6 Reference office building in perspective and floor plan

The annual total electricity results are broken down into different building energy categories, shown in Figure 7. The results of consumption for cooling, lighting, and equipment from the simple hourly model are very close to those simulated by EnergyPlus. However, the simple hourly model has a larger error for consumption by fans and pumps (32% less) and heat rejection (not considered). Overall, the annual total electricity consumption calculated by the simple hourly model is only 2% less than the results from Energy Plus.

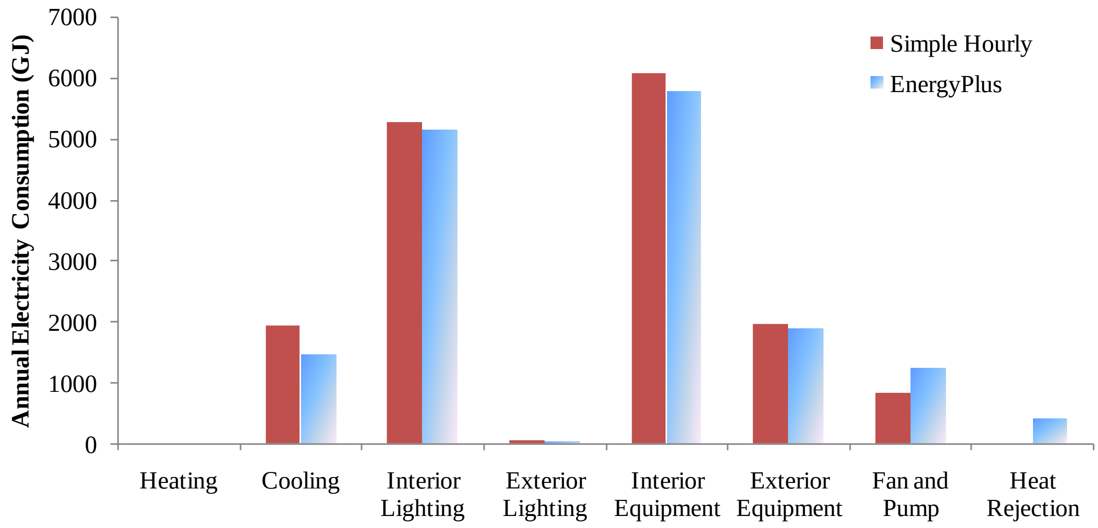


Figure 7 Annual electricity consumption breakdown calculated by EnergyPlus and the simple hourly model

Figure 8, which provides more details, compares the hourly electricity demand over a year calculated by both EnergyPlus and the proposed simple hourly model. The figure shows peak demand during the summer because of the high cooling load. In the winter, the daily load patterns remain relatively regular because the test building uses natural gas as the source for heating. The comparison shows overall compliance between the results of the two methods. However, the simple hourly model underestimates the daily peak load during the intermediate seasons (April–June and October–November) by up to 20%. Moreover, it overestimates the daily peak load during July–August by up to 30%. These differences are mainly a result of the single-zone simplification in the normative model, in which co-existing heating and cooling needs during the intermediate seasons are canceled out. On the contrary, Energy Plus uses a multi-zone simulation model to reflect this effect.

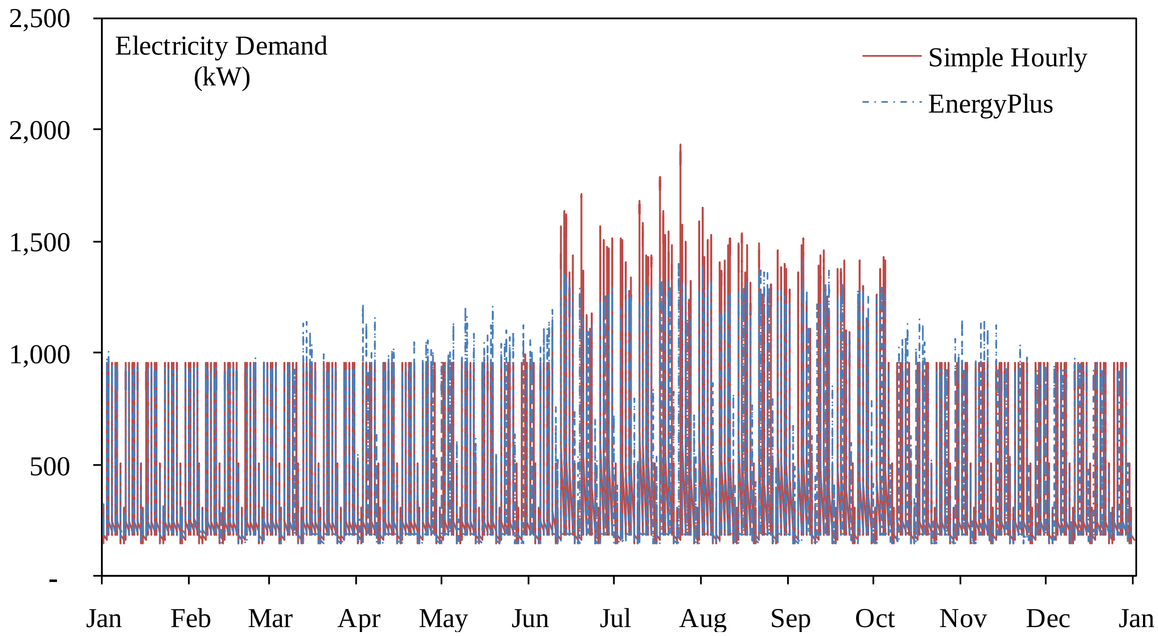


Figure 8 Hourly electricity demand of the reference office building calculated by EnergyPlus and the simple hourly model

The hourly electricity demand for the test building for two typical weeks in January and August are plotted in Figure 9 and Figure 10. The profiles calculated by the two methods resemble each other well in the winter, when there is no cooling demand. In the summer, daily peak demands of the two models slightly differ. In the summer, the difference is approximately 10% for weekdays and as much as 50% for weekends, with an average summer discrepancy of 13.5%.

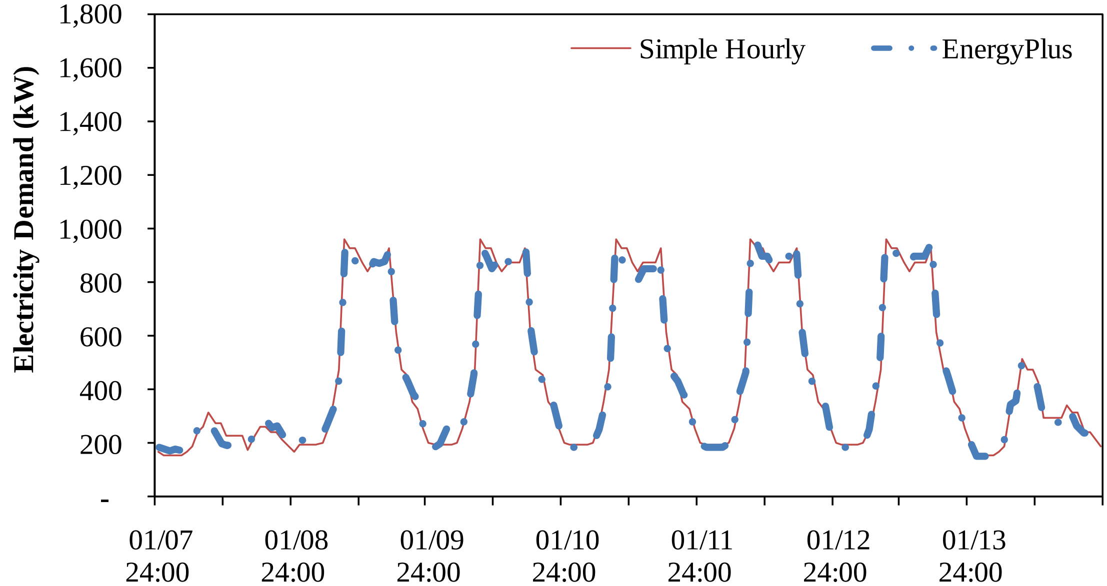


Figure 9 Hourly electricity demand, January 7th through 14th

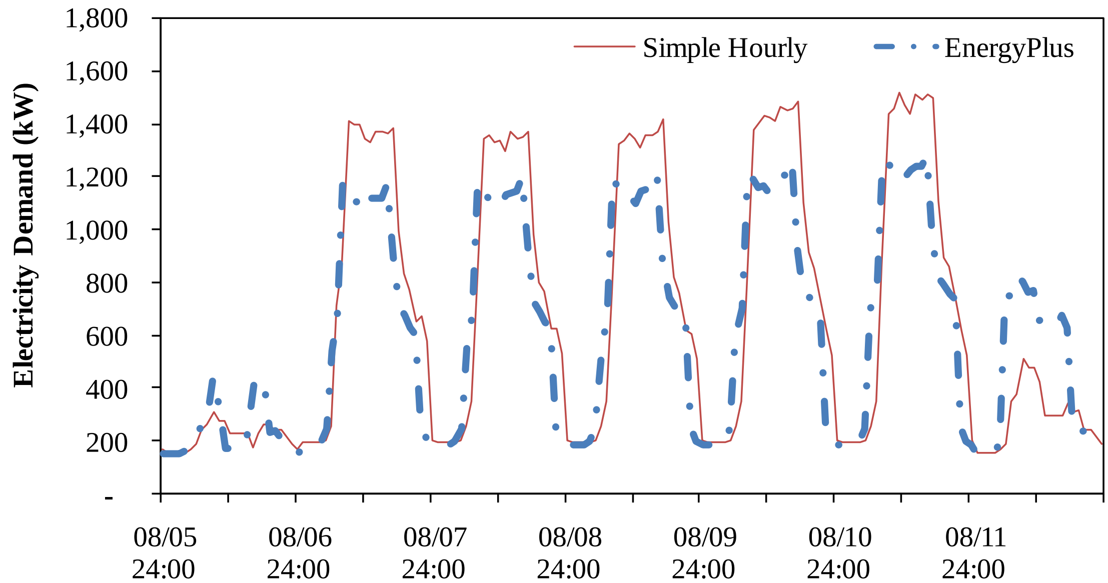


Figure 10 Hourly electricity demand, August 5th through 12th

A comparison of yearly and daily electricity demand profiles shows that the proposed simple hourly model yields a reliable estimate of the annual total demand as well as of diurnal variation for most of the time.

2.5 Concluding Remarks

This chapter begins by describing the normative building energy model and then performs comparative testing and validation of the normative building energy model with Energy Plus. Results of the comparison indicate that despite estimation errors, the normative model returns acceptable results close to the Energy Plus results, and is adequate for the large-scale building stock energy calculation. These tests and validations provide a foundation for commercial building stock modeling.

It is worth noting that these calculation results are based on their actual scenario of use and tends to have almost exactly the same inputs in both models. Thus, the two models are comparable. In practice, normative models are more commonly used as instruments for building performance rating. In such a case, the normative model has to use a standardized scenario of building use so that one can objectively rate how a building is designed regardless of how it is operated. This philosophy is explained in detail by Lee, Zhao, and Augenbroe (2011).

3 SOLVING A DATA-DRIVEN INVERSE PROBLEM TO REPLICATE A BUILDING STOCK

3.1 Introduction

Given a physical system under study, the scientific procedure of researching it can be divided into the following three steps, slightly changed from Meersche, Soetaert, and Oevelen (2009):

1) Observation (*data space*): parameterize the system by identifying a set of observable parameters, and observe results of these observable parameters in an experiment;
2) Forward modeling (*model space*): develop a quantitative abstraction of the relationship between observable parameters and their results from an experiment; and
3) Inverse modeling (*data space to model space*): use the actual observation results to replicate the actual values of model parameters.

For a physical system like the building stock of a city, the observable parameters of it include building design and operational parameters. Two problems are preventing us from performing the inverse modeling to replicate the actual values of these parameters. First, the actual values and distributions of these parameters are typically inadequate due to the exhausted scale of data size and privacy issues. Second, the calculation results (in this case the building energy consumption) using these parameters can only be measured under limited conditions for limited samples. Therefore, these results can only be used in very few situations where they were obtained. Statistical methods are possible candidates to derive the unknowns from the knowns, using large size of data to train a building energy model.

In building stock energy research, information inadequacy of buildings in the stock and the high cost of gathering such information has always been the bottleneck to achieving a higher capability. Tian and Choudhary (2011) proposed a probabilistic method to derive building stock model parameter distributions based on regional energy use data for school buildings in London. Tian and Choudhary's paper has inspired us to use the same statistical technique and apply it to different building types in the U.S.

This chapter demonstrates an approach to replicate the building stock observable parameters using limited national energy consumption survey data. The following three sections are organized accordingly to the abovementioned three steps of researching a physical system proposed by Meersche et al. (2009). Section 3.2 develops a climate adjustment method to derive "measured" building energy consumption data for a city that does not possess sufficient measured energy data. Section 3.3 develops a regression model relating building design/operational parameters and energy consumptions, based on the normative building energy model explained in Chapter 2. Section 3.4 utilizes a linear inverse modeling technique to infer values of model parameters using the results data derived in Section 3.2 and the regression model developed in Section 3.3. Each of the three sections has a hypothesis to be proved.

3.2 Climate Adjustment of Building Energy Consumption Survey Data

Due to high expense of measurement, energy consumption data collection is inadequate for reproducing all descriptive parameters (building design and operational characteristics) and outcome parameters (energy consumption) of any building stock. Building energy consumption surveys have only been conducted to limited amount of buildings at limited amount of locations.

There are two levels of data inadequacy preventing us from fully reproducing the building stock energy profile based on energy survey data. The first level of data inadequacy is within the city scale. Due to lack of data points, the composition of buildings with different characteristics (geometry, material, principle use, etc.) in each location is unknown. Clustering and aggregation of buildings at the city scale have been conducted by in existing literature (Ruchi, 2012; Wittmann, 2007; Yohei Yamaguchi et al., 2007). In the U.S., weighting factors for different building types have been developed by Jarnagin and Bandyopadhyay (2010) for buildings built after 2003, based on construction data in the McGraw-Hill's construction database (McGraw Hill, 2011). All these efforts provide the possibility of using a small portion of buildings, named prototypical buildings or archetypes, to reflect a large population of buildings in a city.

The second level of building stock energy data inadequacy is across individual cities. In most existing cases, building energy survey data are only applicable in a few cities. Another situation, for instance in the U.S., the Commercial Building Energy Consumption Survey (CBECS) database does not even provide cities where sampled buildings are located, but instead only provides general locations (by U.S. census zones), heating degree days (HDD) and cooling degree days (CDD). In these cases, building stock energy profile of a city with inadequate survey data can be extrapolated from the city or region with known energy profile and necessary climate information. This section proposes a regression method and applies it to offices of the U.S. building stock based on the CBECS 2003 database.

Hypothesis 3A: The probability distribution function (PDF) of commercial building energy consumption in a specific city can be extrapolated by a statistical transformation of the energy consumption PDF of a larger area including that city base on climate.

The underlining hypothesis of the abovementioned climate adjustment is described as Hypothesis 3A. The major assumption of this approach is that the distribution of building design and operational characteristics in the city of study has no significant difference from the regional averaged distribution, so that we can "relocate" all sample buildings from their original location to the city of study. In reality, this assumption may not be always true, so that the extrapolated PDF of commercial building energy consumption represents a scenario as "what if we moved all buildings to this city". Given design and operational characteristics of individual buildings and their energy consumption, we can still use this artificially "extrapolated" city for further intervention analysis.

This problem can be states as following. When energy consumption survey results are available for a set of buildings, numbered as i ($i = 1,2, \ldots, \mathbb{N}$), energy outputs and inputs of the dataset can be statistically formulated as

$$PI_i \approx f(\boldsymbol{X}_{design,i}, \boldsymbol{X}_{operation,i}, \boldsymbol{X}_{climate,i}) \,, \qquad (3\text{-}1)$$

where PI_i is an energy performance indicator of building i, for instance, annual delivered electricity, annual primary energy consumption, etc.; $\boldsymbol{X}_{design,i}, \boldsymbol{X}_{operation,i}, \boldsymbol{X}_{climate,i}$ are vectors of design, operation, and climate parameters of building i, respectively. f is a statistical function identical for all buildings in the data set. Given this function, we can then relocate building i to another location and predict the adjusted energy performance indicator, $PI_{i,adj}$, by substituting climate parameters $\boldsymbol{X}_{climate,i}$ with climate parameters from the new location, denoted as $\boldsymbol{X}_{climate,adj}$:

$$PI_{i,adj} \approx f(\boldsymbol{X}_{design,i}, \boldsymbol{X}_{operation,i}, \boldsymbol{X}_{climate,adj}) \;. \qquad (3\text{-}2)$$

Several well-established statistical methods have been used for predicting or assessing building energy consumption, such as simple normalization, general linear regression (also called ordinary least squares), corrected ordinary least squares, stochastic frontier analysis, and data envelopment analysis (Chung, 2011). Although more advanced techniques usually provide more detailed results for critical conditions, the most commonly used statistical method for building stock energy profile estimation is OLS. This is not only because of its simple procedure and intuitive results, but also because of its reliability and robustness advantages compared to other advanced techniques. Tso and Yau (2007) compared three statistical techniques of predicting building energy consumption: regression analysis, decision tree, and neural networks. The authors found that although decision tree and neural networks performed slightly better in winter and summer seasons, differences in these three types of model are minimal, indicating that general linear regression is valid and comparable to the more advanced methods. Therefore, in this study simple linear regression has been chosen. If N observations are collected in an energy survey, the model for them takes the form

$$PI_i = \beta_0 + \beta_1 x_{i,1} + \beta_2 x_{i,2} + \cdots + \beta_k x_{i,k} + \varepsilon_i, \qquad i = 1,2, \ldots, N, \qquad (3\text{-}3)$$

where PI_i is the i th energy performance indicator value, $x_{i,1}, x_{i,2}, \ldots, x_{i,k}$ the corresponding values of the k covariates (such as floor area, building age, energy system, climate data, etc.), $\beta_0, \beta_1, \ldots, \beta_k$ the intercept and slope coefficients to be estimated, and

ε_i the random error of the ith observation. If in a data set each observation represents a collection of identical observations, such as the CBECS database, weighted least squares have to be estimated to solve the regression problem.

Once a regression approach is decided upon, the next essential step is to determine which dependent and independent variables should be considered to construct the regression model. The dependent variable in this proposed model is the building primary energy used intensity, denoted as $EUI_{primary}$ (in kWh/m^2,year). This is equal to the total primary energy use of the building divided by the gross floor area. By setting primary EUI as the dependent variable, the different mixture of electricity, natural gas, and other onsite energy use carriers can be evaluated in an equivalent manner. Primary EUI has also been used in the regression analysis of Energy Star (EPA, 2007) for building performance benchmarking and rating. The independent variables have to cover all important energy-related building characteristics. Monts and Blissett (1982) summarized previous studies and suggested five factors determining the building energy consumption: (1) climate and location of the building, (2) the temperature and humidity desired, (3) the number of occupants and period of occupancy, (4) the thermal performance of the structure itself, and (5) the building use.

To determine which variables have significant effects to the outcome, the next step is variable selection. The goal of variable selection in regression analysis is to identify the smallest subset of the covariates, in this case, the building characteristics parameters. One strategy is the best subset regression, which applies a model selection criterion to all possible subsets and select the subset (which corresponds to a regression model) with the highest adjusted R^2 (Wherry, 1931). Another strategy is the stepwise regression, which combined backward elimination and forward selection to carry out the choice of predictive variables by applying a sequence of F-tests (Wu & Hamada, 2009).

In this section, we take the CBECS 2003 data sets as an example to construct a general linear regression for office buildings in the U.S. This regression model is then used for climate adjustment to extrapolated energy consumption PDF of office buildings in three U.S. cities to test Hypothesis 3A.

3.2.1 Introduction to the CBECS 2003 Database

The Commercial Buildings Energy Consumption Survey (CBECS) is conducted quadrennially by the U.S. Energy Information Administration to provide basic statistical information about energy consumption and expenditures in U.S. commercial buildings and information about energy-related characteristics of these buildings. The survey is based upon a sample of commercial buildings selected according to the sample design requirements described below. A "building," as opposed to an "establishment," is the basic unit of analysis for the CBECS because the building is the energy-consuming unit. The most recent survey, CBECS 2003, was the eighth survey conducted since 1979 and is used in this study (EIA, 2006).

The target population for the 2003 CBECS consisted of all commercial buildings that were larger than 1,000 square feet in the U.S. (with the exception of commercial buildings located on manufacturing sites).

Unfortunately, the finest level of geographic detail that is publicly available in CBECS is the Census division. In addition, building characteristics that could potentially identify a particular responding building, such as number of floors, are also masked to protect the respondent's identity.

3.2.2 Data Filtering

The first step of the regression analysis is to filter out reasonable data from the original CBECS database. Three types of filters are applied sequentially:

1. *Building Type Filters*: As mentioned above, building use has significant impacts on building energy consumption. Thus, each building type deserves a unique regression model. In this example, only office buildings are selected.
2. *Feasibility Filters*: Based on prior knowledge in similar regression analysis, certain variables have significant impacts and should be included for variable selection. These variables of data samples shall indicate "typical" buildings. For instance, a typical building shall be operated for more than 10 months of a year (PBA8 = 2); the building shall be air conditioned (percent cooled > 0, percent heated > 0).
3. *Outlier Filters*: Outlier points shall be eliminated to achieve higher accuracy for common buildings.

We have applied these three sets of filters to the original CBECS 2003 micro data and ultimately come up with 765 office building for this regression analysis. The filtering process is shown in Table 2.

Table 2 Summary of data filters in the regression analysis

Condition for Including an Observation	Rationale	Samples Remaining	Total Bldgs.	Total Floor Area (Mm^2)
All data sets	Data source	5,215	4,858,750	6,664
PBA8=2	Office buildings	976	823,805	1,135
Months in use last year >= 10	A typical building being used	951	788,760	1,116
Percent cooled > 0, Percent heated > 0	Building must be conditioned	911	742,015	1,078
Must have at least 1 person computer	Must be a functional office building	906	730,234	1,076
EUI_Primary <= 1,640 kWh/m2/yr	Eliminate outliers outside [Q1-1.5IQR, Q3+1.5IQR]	866	708,450	1,034
Floor Area <= 30,848 m2	Eliminate outliers outside [Q1-1.5IQR, Q3+1.5IQR]	765	705,123	783

The remaining 765 samples correspond to 705,123 actual buildings according to the weighting factors applied to data samples. Considering weighting factors, histograms of gross floor area, building subtype, climate characteristics, and primary EUI are plotted in the following figures.

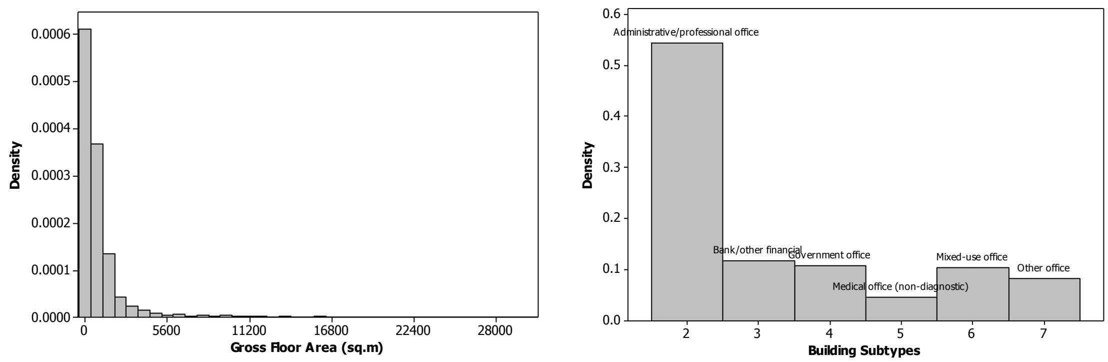


Figure 11 Histogram of building gross floor area and subtypes of selected CBECS 2003 offices

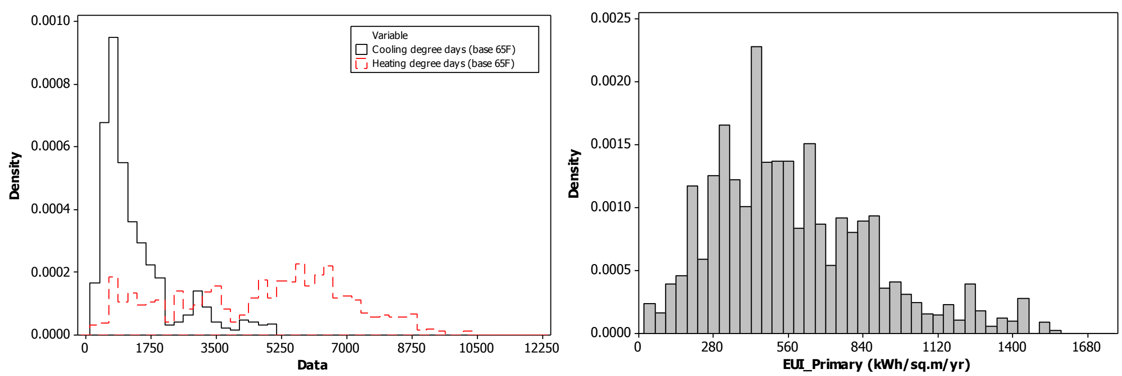


Figure 12 Histogram of HDD, CDD, and primary EUI of selected CBECS 2003 offices

3.2.3 Variable Selection and Multiple Regression Analysis

Many observational variables in CBECS 2003 are potentially relevant to building energy consumption. In this study, 20 variables potentially have direct impact to the primary EUI and thus being considered as candidates for the variable selection. These parameters are listed in Table 3. Note that the number 8 after each variable name in indicates that CBECS 2003 is the 8th survey in the CBECS history.

Table 3 CBECS 2003 variables considered in the regression variable selection

Category	CBECS 2003 Variable Name	Definition
Climate	CDD658	Cooling degree days based on 65 °F
	HDD658	Heating degree days based on 65 °F
	DLIMATE8	Climate zone (30-year average)
Construction	SQFT8	Square footage
	YRCON8	Year of construction
	DAYLTP8	Percentage daylight
	WINTYP8	Window glass type
Usage	COOLP8	Percent of the building that is cooled
	HEATP8	Percent of the building that is heated
	WKHRS8	Total weekly operating hours
	MONUSE8	Months in use in the past 12 months
	NWKER8	Number of employees during main shift
	PCNUM8	Number of personal computers
	SRVNUM8	Number of servers
	PRNTRN8	Number of printers
	COPRN8	Number of photocopiers
	RFGWIN8	Number of walk-in refrigeration units
	RFGOPN8	Number of open refrigerated cases
	RFGRSN8	Number of residential refrigerators
	RFGVNN8	Number of vending machines

A study performed by EPA (2007) suggests that the production of cooling degree days (CDD658) and percent of the building that is cooled (COOLP8) should be considered as one variable, and same for HDD658*HEATP8. Meanwhile, the unit of SQFT8 has been changed from square feet to square meters. Usage variables quantified by numbers of objects are normalized by floor areas, in the unit of number per 1000 square meter floor area. We also noticed that several other variables are highly skewed, so we applied log transformations to them to make them closer to symmetric. Therefore, the transformed parameters listed in Table 4 are used for variable selection. Variable samples are plotted as Figure 13.

Table 4 Variables used in the regression analysis

Var. No.	**Variable Name**	**Definition**
1	Ln(CDD*PC)	Cooling degree days based on 65 °F times percent cooled, in hours
2	HDD*PH	Heating degree days based on 65 °F times percent heated, in hours
3	Climate	Climate zone (30-year average)
4	Ln(1000/FlrArea)	Floor area, in m^2
5	Ln(1000/YrCon)	Year of construction
6	DayLtP	Percentage daylight
7	WinType	Window glass type
8	Ln(WkHrs)	Total weekly operating hours
9	MonUse	Months in use in the past 12 months
10	Ln(WkrDen)	Number of workers per $1000m^2$ floor area
11	Ln(PCDen)	Number of PCs per 1000 m^2 floor area
12	Ln(SvrDen)	Number of servers per 1000 m^2 floor area
13	Ln(PrntrDen)	Number of printers per 1000 m^2 floor area
14	Ln(CoprDen)	Number of photocopiers per 1000 m^2 floor area
15	Ln(RfgWiDen)	Number of walk-in refrigeration units per 1000 m^2 floor area
16	Ln(RfgOpDen)	Number of open refrigerated cases per 1000 m^2 floor area
17	Ln(RfgRsDen)	Number of residential refrigerators per 1000 m^2 floor area
18	Ln(RfgVnDen)	Number of vending machines per 1000 m^2 floor area

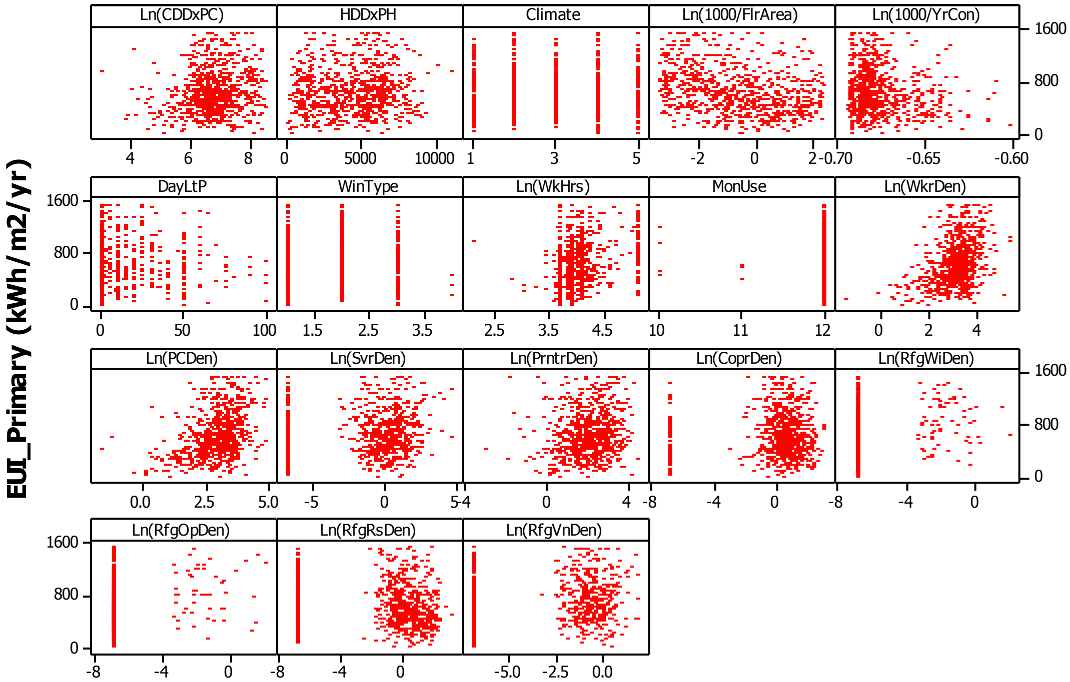


Figure 13 Scatter plot of candidate regression variables

Table 5 Best subset analysis of variable selection

Subset Size	R^2	R^2_a	C_p	S	Variables
10	32.8	31.9	13.9	276.16	1,2,4,5,8,9,11,13,16,18
11	33.1	32.1	12.8	275.77	1,2,4,5,6,8,9,11,13,15,18
12	33.3	32.3	12.1	275.45	1,2,4,5,6,8,9,11,13,15,16,18
12	33.3	32.3	12.4	275.5	1,2,4,5,6,7,8,9,11,13,15,18
13	33.5	32.4	11.8	275.21	1,2,4,5,6,7,8,9,11,13,15,16,18
13	33.5	32.3	12.4	275.32	1,2,3,4,5,6,8,9,11,13,15,16,18
14	33.7	32.4	12.4	275.14	1,2,3,4,5,6,7,8,9,11,13,15,16,18
14	33.6	32.4	13.1	275.27	1,2,4,5,6,7,8,9,11,12,13,15,16,18
15	33.7	32.4	13.7	275.19	1,2,3,4,5,6,7,8,9,11,12,13,15,16,18
15	33.7	32.4	13.8	275.22	1,2,3,4,5,6,7,8,9,11,13,15,16,17,18
16	33.8	32.4	15.3	275.3	1,2,3,4,5,6,7,8,9,11,12,13,15,16,17,18
16	33.8	32.3	15.5	275.33	1,2,3,4,5,6,7,8,9,11,12,13,14,15,16,18
17	33.8	32.3	17	275.44	1,2,3,4,5,6,7,8,9,11,12,13,14,15,16,17,18
17	33.8	32.3	17.2	275.48	1,2,3,4,5,6,7,8,9,10,11,12,13,15,16,17,18
18	33.8	32.2	19	275.62	1,2,3,4,5,6,7,8,9,10,11,12,13,14,15,16,17,18

A stepwise regression analysis has also been conducted and shown the same best subset of regression variables, listed in Table 5, and in Table 6 we also list the coefficients, standard error coefficients, t values, and p values of each regression term.

Table 6 Regression analysis results

Predictor	**Coef**	**SE Coefficient**	**T**	**P**
Constant	-1554.6	420.1	-3.7	0
Ln(PCDen)	97.68	15.16	6.44	0
Ln(RfgVnDen)	20.116	3.269	6.15	0
Ln(RfgOpDen)	46.288	7.575	6.11	0
Ln(WkHrs)	151.66	25.34	5.99	0
Ln(WkrDen)	62.04	16.67	3.72	0
Ln(1000/YrCon)	-2002.4	599.6	-3.34	0.001
HDDxPH	0.015658	0.005118	3.06	0.002
WinType	-34.26	13.08	-2.62	0.009
Ln(CoprDen)	-8.205	3.133	-2.62	0.009
Ln(CDDxPC)	32.48	14.14	2.3	0.022
DayLtP	-0.9002	0.4155	-2.17	0.031
Ln(RfgWiDen)	16.956	9.579	1.77	0.077
1000/FlrArea	6.657	3.838	1.73	0.083

Based on the regression analysis described above, we construct the linear regression formula of the CBECS 2003 office buildings. The design variables of the linear regression are the building characteristics collected by CBECS 2003. The response variable in this case is the primary energy use intensity. This formula is shown as follows.

$$EUI_{primary} = -1554.6 + 62.04Ln(WkrDen) - 6.657Ln\left(\frac{1000}{FlrArea}\right) + 151.66Ln(WkHrs) + 97.68Ln(PCDen) + 20.116Ln(RfgVnDen) + 32.48Ln(CDDxPC) + 0.015658(HDDxPH) + 46.288Ln(RfgOpDen) - 2002.4Ln\left(\frac{1000}{YrCon}\right) - 0.9002DayLtP - 8.205Ln(CoprDen) + 16.956Ln(RfgWiDen) - 34.26WinType$$

To evaluate the effectiveness of a multiple linear regression, the first thing we can do is to check the residuals. Figure 14 plots the cumulative density function of residuals, residuals versus fitted values, the histogram of residuals, and residuals versus observation orders, respectively. From these plots, we can find that the spread of the residuals are the same for all treatments. The residuals are equally distributed on both sides of zero, and approximately form a normal distribution, which is a hypothesis of the regression.

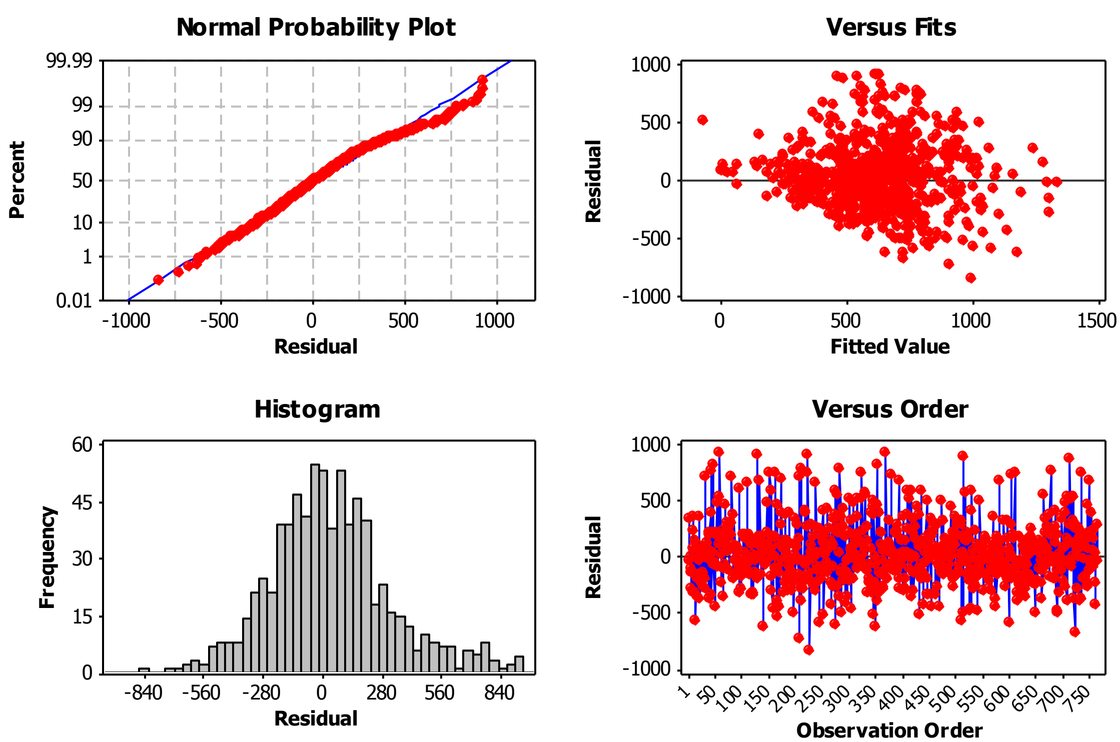


Figure 14 Residual plot of CBECS 2003 office building regression

The second thing we check the regression result is on how well the model can represent the original distribution of building-stock energy consumption. An F-test indicates that the data samples fit in the proposed linear model. This model has an R^2 value that is 34.1%, indicating that this model explains 34.1% of the variance in primary EUI for CBECS 2003 offices. As similarly found in EPA's study (EPA, 2007), a low R^2 value is found for EUI because the explanatory power of floor area is not included in the R^2 value. Re-computing the R^2 value for primary energy in the unit of kWh/year demonstrates that the model actually explains 84.9% of the variance of primary energy consumption. This is an acceptable regression model for building energy prediction. Histograms of measured and fitted primary EUI and primary energy consumption values are shown as in Figure 15 and Figure 16, respectively.

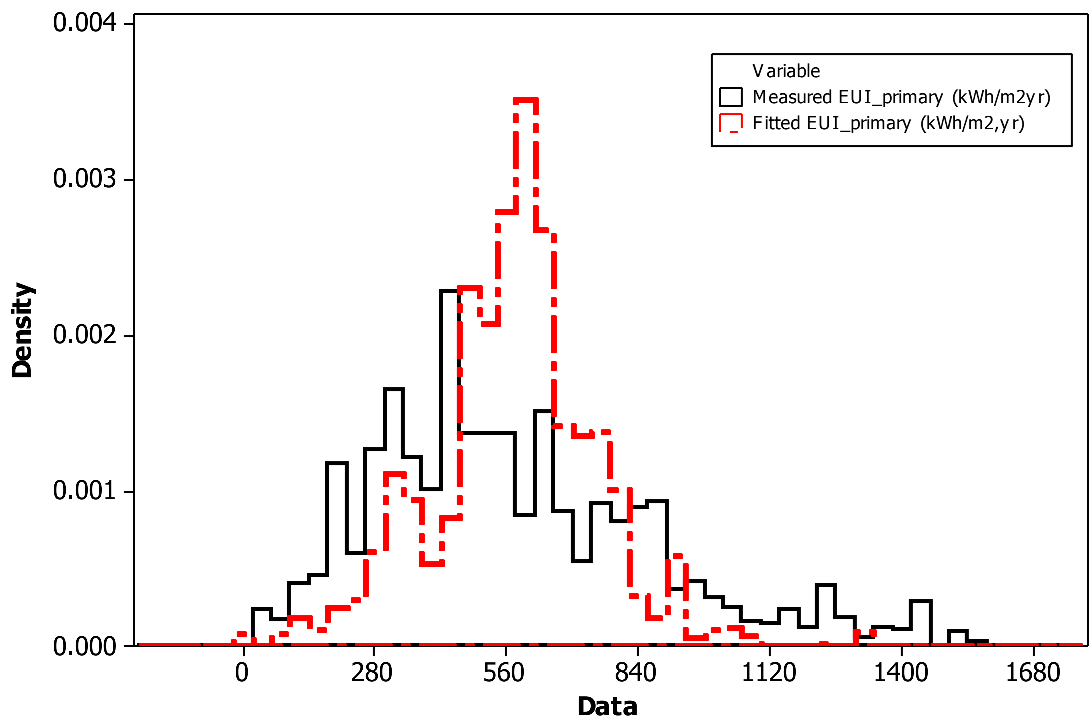


Figure 15 Histograms of measured and fitted primary EUI

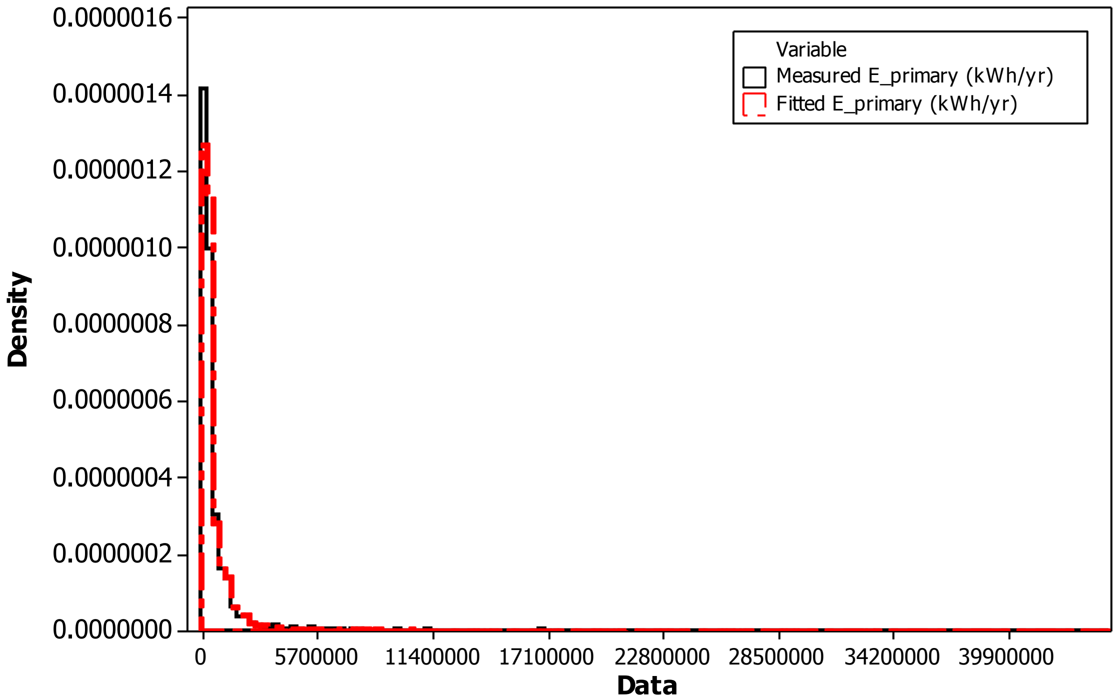


Figure 16 Histograms of measured and fitted primary energy

A two-sample t-test is applied for both measured and fitted primary EUI values and the result indicates that the *mean* values of two data sets are not significantly different from each other (p value = 0.056). The t test also shows that the 95% confident interval is (-0.63982, 52.158), meaning that one can be 95% sure that the true difference (measured minus fitted) between two means is between -0.63982 and 52.158, which is a relatively small range.

Meanwhile, we also apply a two-sample Kolmogorov-Smirnov (K-S) test to two primary EUI datasets to test if their distributions significantly differ. The K-S test has the advantage of making no assumption about the distribution of data because it is non-parametric and distribution free. In this case, the K-S test result rejects the null hypothesis: the two samples are drawn from the same distribution, with a K-S test statistic 0.152. In fact, the standard deviation of measured primary EUI is almost twice as large as the standard deviation of fitted primary EUI. Thus, we can only use the proposed linear model to estimate the mean of primary EUI of a building stock, but cannot reliably replicate the PDF of primary EUI. This result does not prevent us from estimating the overall EUI of a building stock. When a reasonable baseline is established, percentage in energy savings of a building stock can also be estimated.

Another two-sample K-S test has been applied to primary energy consumptions of two samples, and indicates that there is not enough evidence to reject the null hypothesis: the two samples are drawn from the same distribution, with a K-S test statistic 0.033. This means that the *distributions* of primary energy consumption are found to be the same. The two-sample t-test for measured and fitted primary energy consumption values indicates that the means and standard deviations of two data sets are both not significantly different from each other, respective, with a p-value 0.190 for means and a p-value 0.125 for standard deviations. The t-test results indicate that PDFs of measured and fitted primary energy consumption values are statistically identical, assuming that both of them are normal distributions. This result is plausible and can be further used to predict building stock energy performance distribution in the U.S.

3.2.4 Climate Adjustment for CBECS 2003 Offices

To test the climate adjustment transformation model, we apply CDD and HDD values of three cities in the U.S (Table 7), representing cold, mild, and hot climate zones. These three cities are shown on Figure 17.

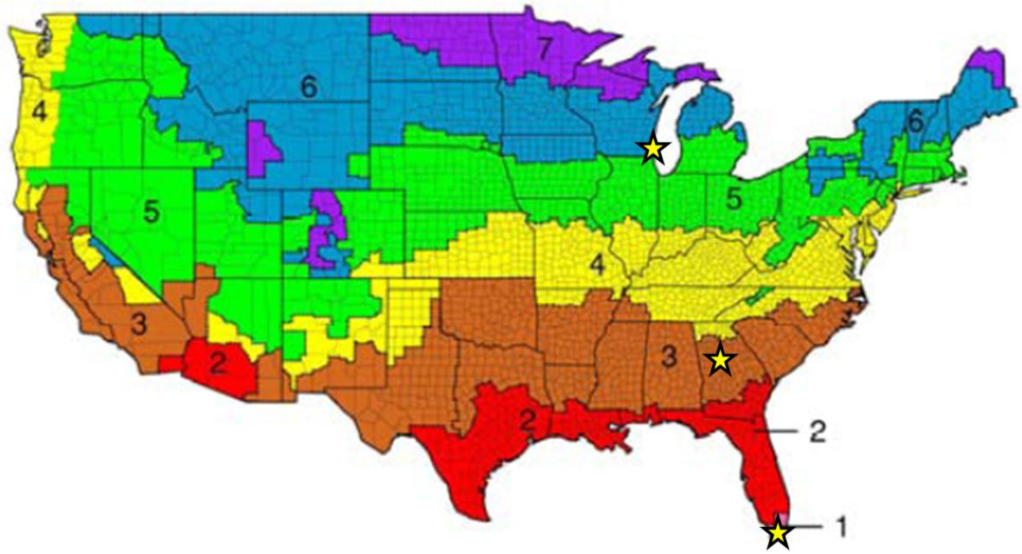


Figure 17 Three test cities on the ASHRAE climate zones map

To compare the predicted primary EUI distribution and "measured" data, we use the range of ±500 CDD and ±500 HDD to select CBECS 2003 raw data, and assume the selected data represent measured data. The abovementioned CDD, HDD, and ranges are listed in Table 7. A comparison of cumulative distribution functions (CDF) of measured and predicted primary EUI in Chicago is plotted in Figure 18.

Table 7 CDD and HDD of three cities

City	CDD	CDD range from CBECS 2003	HDD	HDD range from CBECS 2003
Chicago, IL	691	191 1191	3106	2606 3606
Atlanta, GA	1017	517 1517	1508	1008 2008
Miami, FL	4198	3698 4698	200	0 700

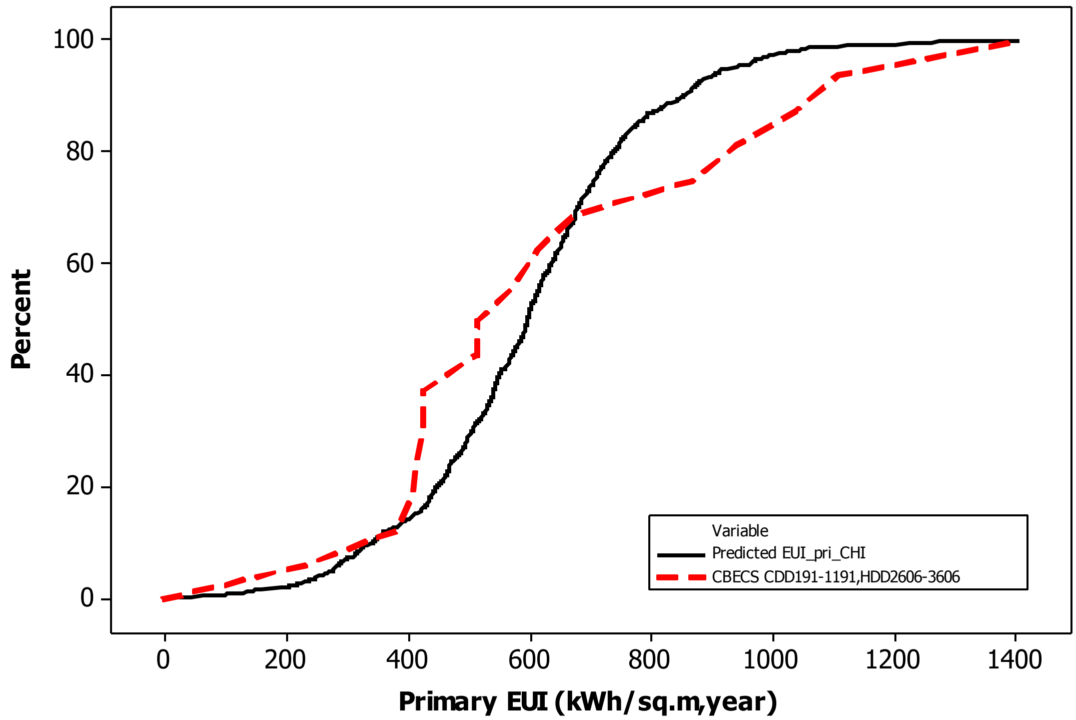


Figure 18 Chicago: Measured vs. predicted primary EUI CDF

A two sample t-test for the mean gives a p-value 0.450, which means the mean of 16 CBECS samples close to Chicago (CDD 191-1191, HDD 2606-3606) is not significantly different from the mean of predicted primary EUI for Chicago (CDD 692, HDD 3106) using the linear regression model. Similar to the primary EUI PDF prediction at national level, t-test also suggests that the standard deviation of predicted data is significantly different from CBECS measured data. Same results have also been found for Atlanta and Miami. Measured and predicted primary EUI CDFs of Atlanta and Miami are plotted as in Figure 19 and Figure 20.

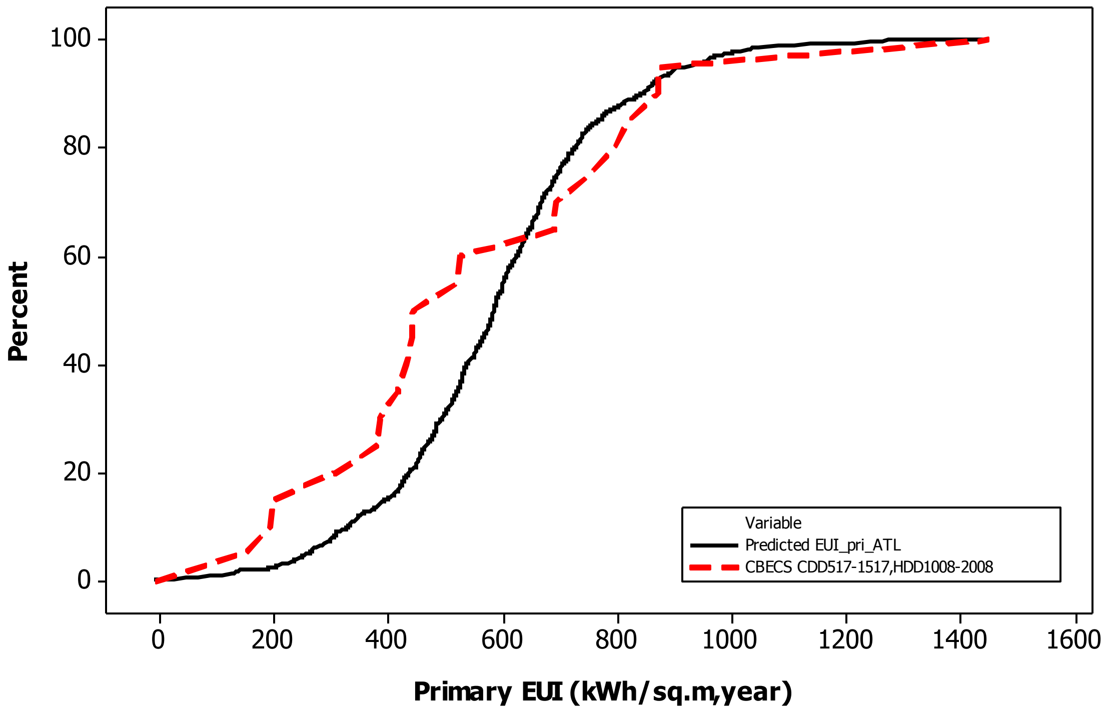


Figure 19 Atlanta: Measured vs. predicted primary EUI CDF

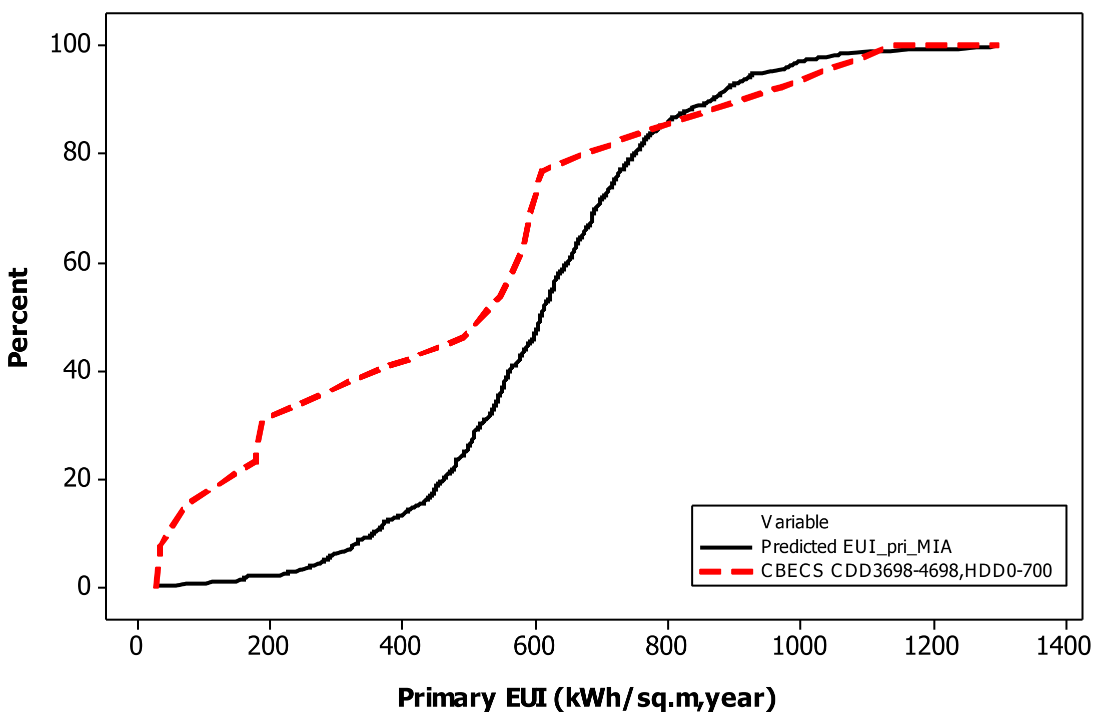


Figure 20 Miami: Measured vs. predicted primary EUI CDF

3.2.5 Findings of This Section

In this section, we have come up with a multiple linear regression to adjust climate conditions in the CBECS database. The purpose of this task, as stated previously, is to generate more measured data to cities that do not poccess enough energy survey data.

The test restuls of this section have partly proved Hypothesis 3A. For primary EUI regression, only the mean value of the data set can be reproduced by the regression model. However, for primary energy consumption, both the mean value and the probablity density distribution of the data set can be reproduced by the regression model. Although not perfect, this result is still sufficient to prove the feasibility of the proposed method in adjusting the climate feasure of building stock survey data, because the mean value of the building stock energy performance is enough to support energy efficiency policy analysis and demand response financial analysis.

The result of this section will be used in the Section 3.4 as measured data to derive model input parameters. The feasibility of the model presented in Section 3.4 is independent from the accuracy of the model presented in this section. When better data are measured in the city under analysis, the climate adjustment step is no longer necessary, but the step in Section 3.4 is still capable of performing the analysis.

3.3 Linear Regression of the Normative Building Energy Model

Input parameters for a dynamic simulation model are typically at the scale of hundreds or thousands. Scalability is a big problem preventing us from using such dynamic simulation models for large scale building stock analysis. Recent building stock modeling work conducted by NREL (Griffith et al., 2008; Leach, Lobato, Hirsch, Pless, & Torcellini, 2010) and PNNL (Thornton, Wang, Huang, Lane, & Liu, 2010) for office buildings have used EnergyPlus as the underlining engine. These models achieved deep details, yet required super computers to compute the results. The normative building energy, as introduced in Chapter 2, is a reliable alternative for this purpose because of its scalability and transparency. Since this sector develops a linear regression of the building energy model for based on large input ranges and large amount of data sample requirement, we use the normative energy model as the baseline to conduct the linear regression.

Hypothesis 3B: Given feasible ranges of building design parameters, a set of inputs and the output (primary EUI) of the normative building energy model can be expressed as a linear regression model.

The underlining hypothesis of this section is described as Hypothesis 3B. The assumption is that the normative energy model is a good representation of the relationship between building design/operational characteristics and building energy consumption. Validation of the normative model has been conducted against EnergyPlus in Chapter 2. However, as suggested by IEA (Heo, 2011), one of the most significant barriers for achieving substantial building energy efficiency improvements is the lack of knowledge about the factors determining energy use. One should not target replicating measured energy consumption data using any type of building energy model without fully considering the “unknowns”, let along predicting actual building energy consumption. In this study, we use the normative building energy model as an instrument to perform comparative analysis for decision support. The specific hypothesis will be explored in Chapter 4.

This section takes office buildings in the U.S. as an example to generate a linear regression model of the building energy model for inverse analysis in Section 3.4.

3.3.1 Variable Ranges

The normative building energy model has many parameters that may not be sensitive to the energy calculation result. The first step of the regression analysis is to apply a sensitivity analysis to a set of parameters that may have significant impacts. Table 8 lists the selected model parameters, their ranges, and references.

3.3.2 Sensitivity Analysis of Normative Model Variables

Given the feasible ranges of model variables, the next step is to generate data samples and retrieve the corresponding model outcomes for variable sensitivity analysis. In this research area, there are two main approaches to determine the sensitivity of input parameters to outputs of a building energy model: local sensitivity analysis and global sensitivity analysis. Local sensitivity analysis, also called the one-factor-at-a-time method, has been used in studies (de Wit, 2001; Heo, 2011) whose goal is to determine the impact of uncertain parameters to the model output in a specific design scenario of a specific building. These studies are more interested in the influence of input factors around a point (De Wilde & Tian, 2010), and have relatively narrow parameter ranges. A commonly used technique is the method of Morris (Morris, 1991). On the contrary, global sensitivity analysis is more interested in robustly estimate importance of input variables over a wide range, usually across a group of buildings. Common techniques include parametric methods such as multiple linear regression coefficients, and nonparametric methods such as multivariate adaptive regression splines (Tian & Choudhary, 2011). This study apparently falls into the global sensitivity analysis because of its large scale. Multiple linear regression analysis is used to rank the importance of parameters.

Table 8 Sensitivity analysis of normative model parameters

	Model Parameters	Unit	Range	References
Form	P01GrossFloorArea	m^2	93.1-30,848	Selected CBECS 2003 office samples
	P02BldgHeight	m	4-50	Selected CBECS 2003 office samples
	P03FloorHeight	m	3.9-4.2	(Kohn & Katz, 2002)
	P04AspectRatio	-	1.5-15	(Leach et al., 2010)
	P05WWR	-	0-1	
Envelope	P06RoofUValue	W/m2K	0.2-1.5	(Macdonald, 2002)
	P07RoofAbsCoef	-	0.43-0.83	(Macdonald, 2002)
	P08RoofEmissivity	-	0.87-0.95	(Macdonald, 2002)
	P09WallUValue	W/m2K	0.2-1.5	(Macdonald, 2002)
	P10WallAbsCoef	-	0.43-0.83	(Macdonald, 2002)
	P11WallEmissivity	-	0.87-0.95	(Macdonald, 2002)
	P12WindowUValue	W/m2K	1.5-4	(Macdonald, 2002)
	P13WindowSolarTrans	-	0.16-0.26	(Loutzenhiser, Manz, Moosberger, & Maxwell, 2009)
	P14AirLeakageACH	ACH	0.1-1.25	(Heo, 2011)
	P15EnvelopeHeatCap	J/m2K	80,000-370,000	(ISO, 2008)
Internal Gain	P16Occupancy	M2/p	4.93-744	Selected CBECS 2003 office samples
	P17MetabolicRate	W/p	70-425	(Macdonald, 2002)
	P18AppliancesTotal	W/m2	0-34	Upper bound based on (Dunn & Knight, 2005)
	P19IntLitPowerIntensity	W/m2	0-17	Upper bound based on (CIBSE, 2006)
Control	P20HeatingTSetOcc	℃	17-25	(Tian & Choudhary, 2011)
	P21HeatingTSetUnocc	℃	17-25	(Tian & Choudhary, 2011)
	P22CoolingTSetOcc	℃	17-25	(Tian & Choudhary, 2011)
	P23CoolingTSetUnocc	℃	17-25	(Tian & Choudhary, 2011)
HVAC	P24CoolingSystemPLV	-	0.83-0.99	(Hu, 2009)
	P25AlphaCool	-	0-0.15	(BSi, 2007a)
	P26AlphaHeat	-	0-0.36	(BSi, 2007a)
	P27DHWGenSysEff	-	0.88-0.95	(Healy, Lutz, & Lekov, 2003)
	P28DHWDistriSysEff	-	0.54-0.66	(BSi, 2007b)
	P29CoolingCOP	-	2.5-5.9	(ON, 2007)
	P30HeatingEff	-	0.7-0.9	(Tian & Choudhary, 2011)

The Monte Carlo (MC) simulation is used to firstly generate samples for the regression analysis. The MC simulation is a method to analyze how much random variation of variables can affect the system performance. It generates random numbers to model stochastically create event occurrences. In order to better represent the variation of the multidimensional parameter space without overwhelming the quantity of samples, an efficient way for data sampling is to use the Latin Hypercube Sampling (LHS) technique instead (McKay, Beckman, & Conover, 1979). A Latin hypercube is the generalization of this concept to an arbitrary number of dimensions, whereby each sample is the only one in each axis-aligned hyper-plane containing it. Thus, LHS "fills" the parameter space better and converges faster compared to the classic Monte Carlo sampling.

Only a large enough number of samples can fully represent the randomness of the nature. By the law of large numbers, this method will display $1/\sqrt{N}$ convergence—i.e., quadrupling the number of sampled points will halve the error, regardless of the number of dimensions (Press, Teukolsky, Vetterling, & Flannery, 1996). One index to evaluate the adequacy of a MC sample size was proposed by Billinton and Li (1994) and used in evaluating a stochastic building energy model by Hu (2009):

$$CoV = \frac{\sigma}{E(PI)} \tag{3-4}$$

where,

CoV is the coefficient of variance (CoV) expressing the accuracy level of a MC simulation;

$E(PI)$ the estimated expectation of the model performance indicator (PI); and

σ the standard deviation of the generated $E(PI)$ based on a sample size.

The CoV value can be interpreted as the percentage of error in the estimated performance indicator due to randomness of the LHS simulation process. In this study, we gradually increase the number of LHS sample size, from 20 to 3,000. Under each sample size we run the LHS ten times and compute the σ value of the ten PIs from the simulation. This convergence check generates the result as in Figure 21.

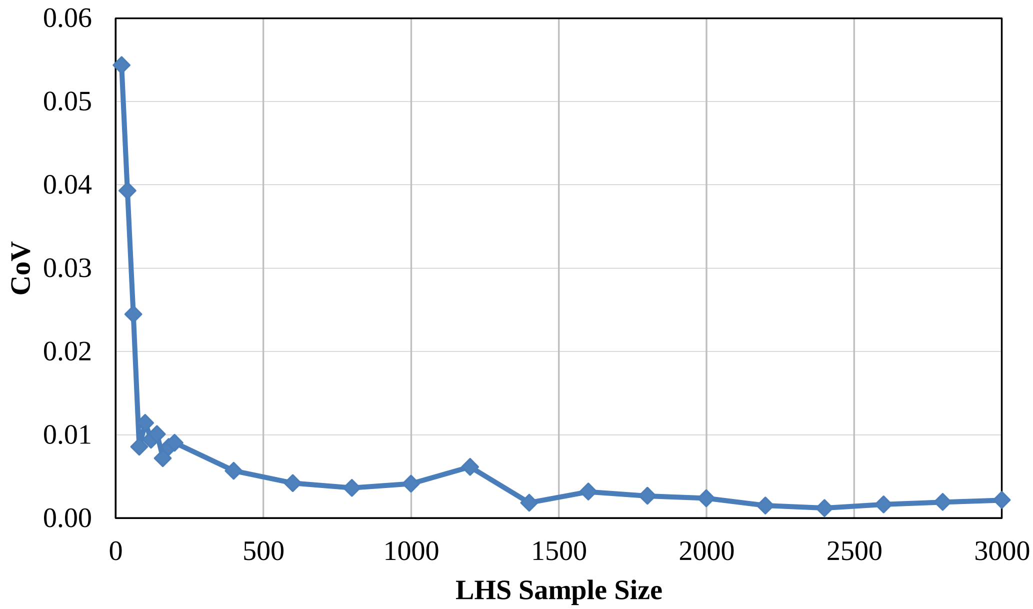


Figure 21 The CoV values of primary EUI corresponding to different LHS sample sizes

The LHS convergence test shown in Figure 21 indicates that the CoV value goes below 0.01 and maintains relatively stable when sample size is larger than 500, and especially stable after 1,500. Since 1% is an acceptable error in the building energy modeling context, a sample size of 1,000 will meet the accuracy requirement of the MC simulation. Therefore, 1,000 sample points, every one of which is an instance of the 30 variables in Table 8, have been generated by LHS. Since the outcome of the energy model is energy use intensity which is a parameter normalized by building gross floor area, variable P01GrossFloorArea is transformed to 10^6/P01GrossFloorArea for the regression analysis. Besides, variable P29CoolingCOP and P30HeatingEff are transformed to 10/P29CoolingCOP and 10/P30HeatingEff respectively due to their nature in the end use energy calculation.

The 1,000 samples are fed into the normative model to compute their corresponding primary EUI values using Chicago weather data. The original samples and their corresponding primary EUI values are then used in a stepwise regression analysis (introduced in Section 3.3) for parameter sensitivity analysis. Table 9 lists the sensitivity analysis result.

Table 9 Sensitivity analysis of variables under the Chicago climate

No. of Var.	Variable	t	p	R^2	R^2(adj.)
1	P18AppliancesTotal	83.74	0.00	62.33	62.29
2	P19IntLitPowerIntensity	32.40	0.00	72.17	72.12
3	1e6/P01GrossFloorArea	31.32	0.00	78.25	78.18
4	P05WWR	23.28	0.00	82.45	82.38
5	10/P29CoolingCOP	15.92	0.00	84.59	84.51
6	P22CoolingTSetOcc	-14.96	0.00	86.38	86.29
7	P02BldgHeight	14.66	0.00	87.88	87.79
8	P20HeatingTSetOcc	13.57	0.00	89.27	89.18
9	P04AspectRatio	11.14	0.00	90.13	90.04
10	P14AirLeakageACH	9.33	0.00	90.87	90.78
11	P09WallUValue	6.87	0.00	91.38	91.29
12	**P06RoofUValue**	**6.08**	**0.00**	**91.74**	**91.64**
13	P12WindowUValue	5.78	0.00	91.96	91.85
14	P16Occupancy	-3.76	0.00	92.09	91.97
15	P15EnvelopeHeatCap	-3.65	0.00	92.18	92.06
16	P21HeatingTSetUnocc	3.49	0.00	92.28	92.15
17	P26AlphaHeat	2.88	0.00	92.36	92.23
18	P24CoolingSystemPLV	-3.10	0.00	92.43	92.29
19	P25AlphaCool	3.07	0.00	92.49	92.34
20	P23CoolingTSetUnocc	-2.27	0.02	92.53	92.37
21	P07RoofAbsCoef	2.22	0.03	92.56	92.40
22	P08RoofEmissivity	-1.62	0.11	92.58	92.41
23	P13WindowSolarTrans	1.64	0.10	92.60	92.43
24	P03FloorHeight	1.56	0.12	92.62	92.44

In Table 9, 24 out of the 30 candidate variables form the best subset, leaving out 6 other parameters. Adding any additional variables would reduce the adjust R^2 value. These 24 variables are ranked by their absolute t statistic values (negative t values indicate that the primary EUI would increase if these variables decrease, and vice versa). The higher the absolute value of t, the more significant is the coefficient of that variable. Meanwhile, the R^2 values achieved by each number of variables are also listed in the table. 92.62% is the highest R^2 that can be achieved using all the 24 variables, meaning that 92.62% of the total variance can be explained by the regression model constructed by these 25 variables. Since the R2 value only increases marginally after exceeding 90% (as shown in Figure 22), we choose the first 12 variables in this study to reduce computational power. The top 12 variables can explain 91.74% of the total variance.

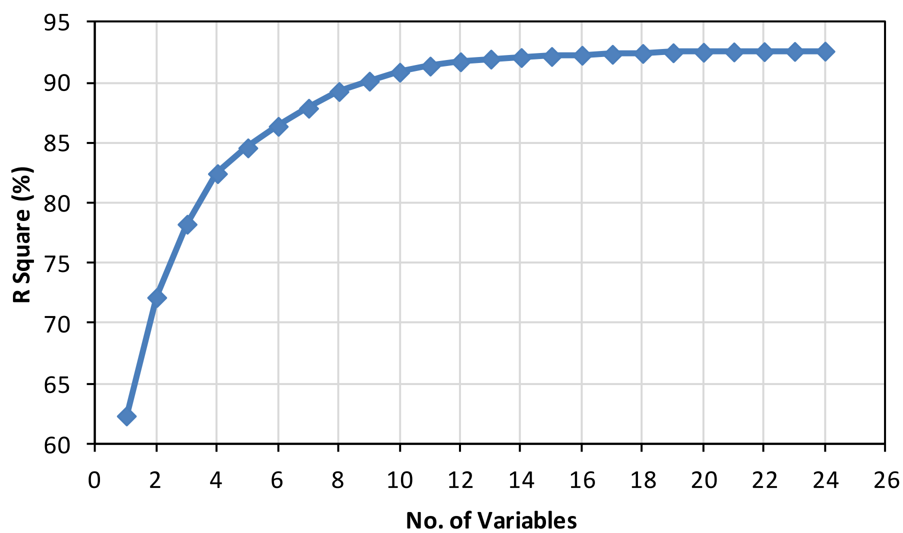


Figure 22 Results of stepwise analysis for variable selection: R^2 vs. No. of variables

Based on these 12 variables, the multiple linear regression model representing the normative building energy model under the Chicago climate is:

$$
\begin{aligned}
EUI_{primary} = & -154 + 16.6\, P18AppliancesTotal + 12.4\, P19IntLitPowerIntensity \\
& + 0.307 \times 1e6/P01GrossFloorArea + 167\, P05WWR + 48.8 \\
& \times 10/P29CoolingCOP - 12.9 P22CoolingTSetOcc \\
& + 2.03\, P02BldgHeight + 10.7 P20HeatingTSetOcc \\
& + 5.77 P04AspectRatio + 51.8 P14AirLeakageACH \\
& + 37.8 P09WallUValue + 30.1 P06RoofUValue
\end{aligned} \tag{3-5}
$$

To evaluate the regression model in terms of how well it replicates the original sample distribution, a two-sample K-S test has been conducted to normative model generated and regression fitted data sets. The K-S statistic returns a value of 0.025, which indicates that there is no sufficient evidence to conclude that the underlying distributions are different. The histograms of two data sets are plotted in Figure 23. In addition, Figure 24 shows the alignment of modeled and fitted results. Both figures indicate that the regression results sufficiently reflect the overall distribution as well as individual sample values of the normative building energy model.

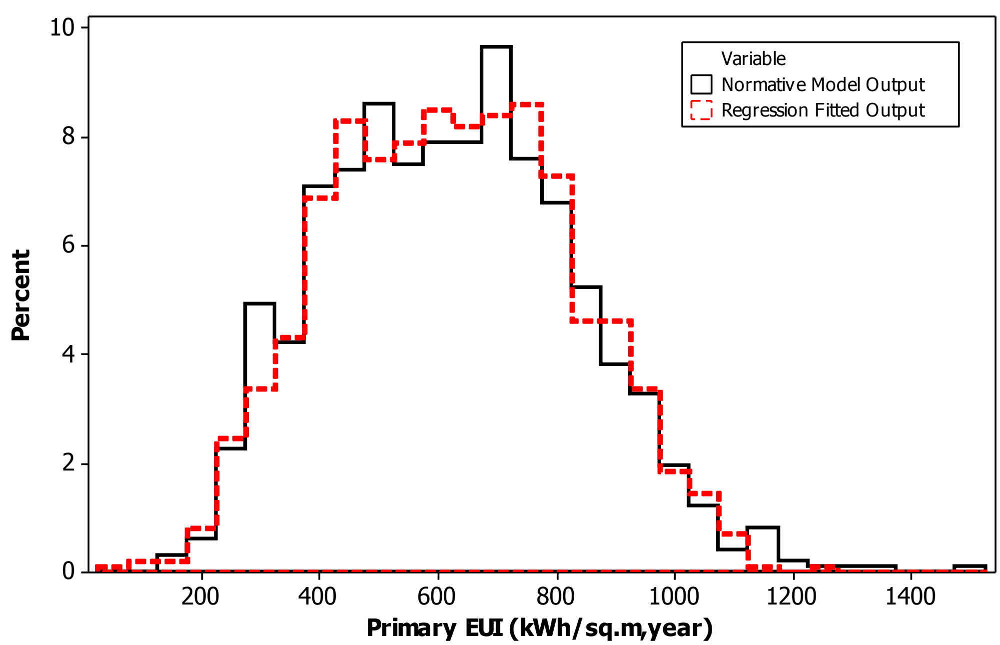


Figure 23 Histograms of normative model generated against regression fitted primary EUI for Chicago offices

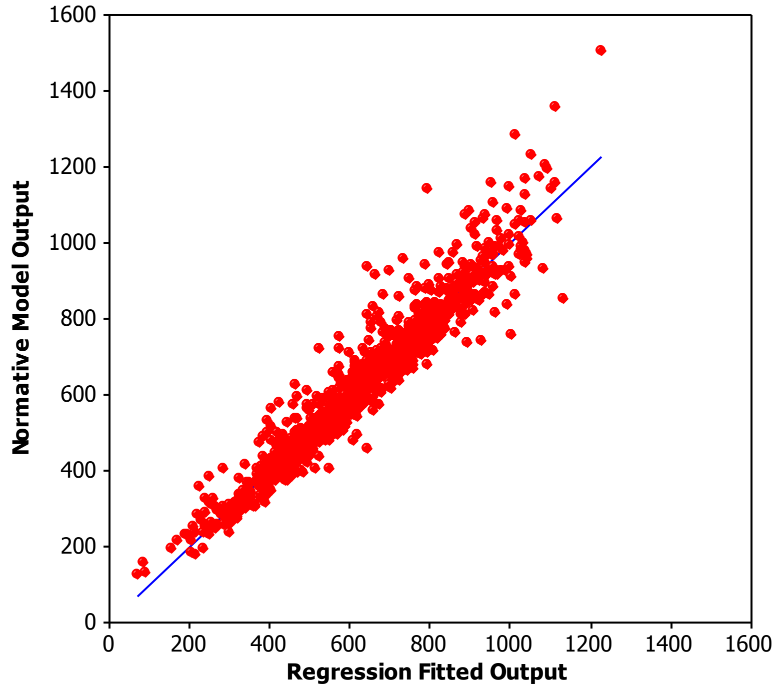


Figure 24 Primary EUI (in kWh/m^2,year): Regression fitted outputs against normative model outputs

3.3.3 Findings of This Section

There is enough evidence to prove that the normative building energy model can be represented by a linear regression model. Hypothesis 3B is a fact with an acceptable margin. This linear model will then be used as the relationship between building model inputs and outputs to solving the inverse problem.

Thus, this linear regression model can be further used in an inverse problem to represent a more sophisticated energy model.

3.4 Solving a Linear Inverse Problem to Replicate the Building Stock

On the basis of building energy performance (i.e., primary EUI) distribution in a city and a linear regression of building energy model identified in the previous sections, the next step of replicating the building stock is to derive design and operational parameters of buildings in that city. Different from typical energy modeling process, this problem is defined as: "knowing the outputs of a model, how do we derive the inputs?" This type of problem is defined as an *inverse problem*. The hypothesis to be tested in this section is as follows.

Hypothesis 3C: Given (1) the distribution of building primary EUI in a city and (2) a linear estimation of a building energy model, one could solve a linear inverse problem to generate distributions of the building energy model input variables, which can replicate the building stock primary EUI distribution.

3.4.1 Inverse Problems

Consider the following model[3]

$$\boldsymbol{y} = f(\boldsymbol{\beta}, \boldsymbol{X}) \tag{3-6}$$

where

$\boldsymbol{\beta}$ is the model parameter vector;

$\boldsymbol{X}$ the input variable matrix; and

$\boldsymbol{y}$ the output variable vector.

A *forward problem* is defined as: Given the parameter matrix $\boldsymbol{\beta}$, what are the values of $\boldsymbol{y}$ for $\boldsymbol{X}$?

On the contrary, an *inverse problem* is defined as: Having data $(\boldsymbol{X}, \boldsymbol{y})$, how to calculate or estimate the parameter vector $\boldsymbol{\beta}$? Another form is that having data $(\boldsymbol{\beta}, \boldsymbol{y})$, how to calculate or estimate the variable matrix $\boldsymbol{X}$? In this chapter, we are dealing with the second form to estimate building design and operational variables $\boldsymbol{X}$.

[3] Notations: Vectors and matrices are in bold; scalars in normal font. Vectors are indicated with a small letter; matrices with capital letter.

3.4.2 Solving Linear Inverse Problems

As a special inverse problem, if the function f is a linear function so that there is no interaction between elements of $\boldsymbol{x}$, the inverse problem is a *linear inverse problem*. A linear model is typically written in matrix notation as $\boldsymbol{Ax} = \boldsymbol{b} + \epsilon$, where $\boldsymbol{x}$ a vector of variables, and ϵ an error vector. A general formulation of a linear model considering additional equality and inequality constraints can be expressed as:

$$\begin{cases} Inequality\ constraints: \boldsymbol{Ax} = \boldsymbol{b} + \epsilon \\ Equality\ constraints: \boldsymbol{Ex} = \boldsymbol{f} \\ Inequality\ constraints: \boldsymbol{Gx} \geq \boldsymbol{h} \end{cases} \tag{3-7}$$

An inverse problem is usually under-determined or over-determined. In Equation (3-7), $\boldsymbol{A}$ is an $m \times n$ matrix and $\boldsymbol{x}$ is an $n \times 1$ vector. If $m < n$, meaning that there are more unknown variables than equations, the system is *underdetermined* and usually has infinite solutions. Monte Carlo sampling methods can be used to sample the feasible region of an underdetermined linear problem in a uniform way (R. L. Smith, 1984). The term ϵ can then be considered as the uncertainties in the data.

On the contrary, if $m > n$, meaning that there are more equations than unknown variables, the system is *overdetermined* and usually there is no solution for which $\epsilon = 0$. An over-determined linear model can be solved by minimizing a norm of the error term $\epsilon = \boldsymbol{Ax} - \boldsymbol{b}$, for example the sum of squares $\sum \epsilon^2$. In this case, the term ϵ represents a model error term rather than uncertainties in the data.

This study uses an algorithm proposed by Meersche et al. (2009) to solve the overdetermined linear inverse problem. The algorithm contains two steps: (1) eliminate the equality constraints $\boldsymbol{Ex} = \boldsymbol{f}$ and (2) perform a random walk on the reduced problem.

In the equality elimination step, $\boldsymbol{x}$ elements in the exact equality $\boldsymbol{Ex} = \boldsymbol{f}$ are linearly transformed to a vector $\boldsymbol{q}$ so that all elements are linearly independent. This linear transformation merges the exact equality constraints $\boldsymbol{Ex} = \boldsymbol{f}$ the approximate equality constraints, so the problem is reduced to

$$\begin{cases} \boldsymbol{A}'\boldsymbol{q} - \boldsymbol{b}' = \epsilon \\ \boldsymbol{G}'\boldsymbol{q} - \boldsymbol{h}' \geq 0 \end{cases} \tag{3-8}$$

where $\boldsymbol{A}', \boldsymbol{b}', \boldsymbol{G}', \boldsymbol{h}'$ are linearly transformed forms of $\boldsymbol{A}, \boldsymbol{b}, \boldsymbol{G}, \boldsymbol{h}$. In this transformed problem, one can randomly sample $\boldsymbol{q}$ without meeting any exact equality constraints.

In the random walk step, the Markov chain Monte Carlo (MCMC) sampling method has been used. For high-dimensional problems, the MCMC random walk is much more efficient than a grid-based sampling method. In the MCMC process, new samples (denoted as $\boldsymbol{q_2}$) are randomly drawn from a jump distribution *j* with a PDF $j(\cdot\,|\boldsymbol{q_1})$ that only depends on the previous accepted point, $\boldsymbol{q_1}$. The new sample point $\boldsymbol{q_2}$ is then either accepted or rejected based on the following satisfaction criterion (Meersche et al., 2009):

$$if\ r \leq \frac{p(\boldsymbol{q_2})}{p(\boldsymbol{q_1})}\ accept\ \boldsymbol{q_2}, \qquad else\ keep\ \boldsymbol{q_1} \tag{3-9}$$

with $0 < r < 1$ the satisfaction ratio and $p(\cdot)$ the PDF of the target distribution. Thus, the MCMC method can be used to approximate the posterior density functions after adequate number of interactions. In this study, the “coordinate directions algorithm (CDA)” is used for the random walk. The CDA algorithm (R. L. Smith, 1984) first selects a direction along one of the coordinate axes, and the new sample obtained by uniformly sampling the line connecting the old sample and the old sample and the intersection with the plains defined by the inequality constraints.

The R (R Development Core Team, 2008) function xsample() (Meersche et al., 2009) is used in this study. xsample() is currently part of the limSolve package (K, K, & D, 2009).

3.4.3 Implementation: A Test Case for Chicago Office Buildings

The test case uses the derived samples of primary energy use intensity (EUI, in the unit of kWh/m^2, year) of Chicago offices, serving as the "measured" distribution of the $\boldsymbol{d}$ vector in Equation (3-7). The regression model for Chicago generated in Section 3.3 is used in the linear inverse problem. Feasible ranges of the ten variables distributions of which being estimated are the same as their original ranges listed in Table 9.

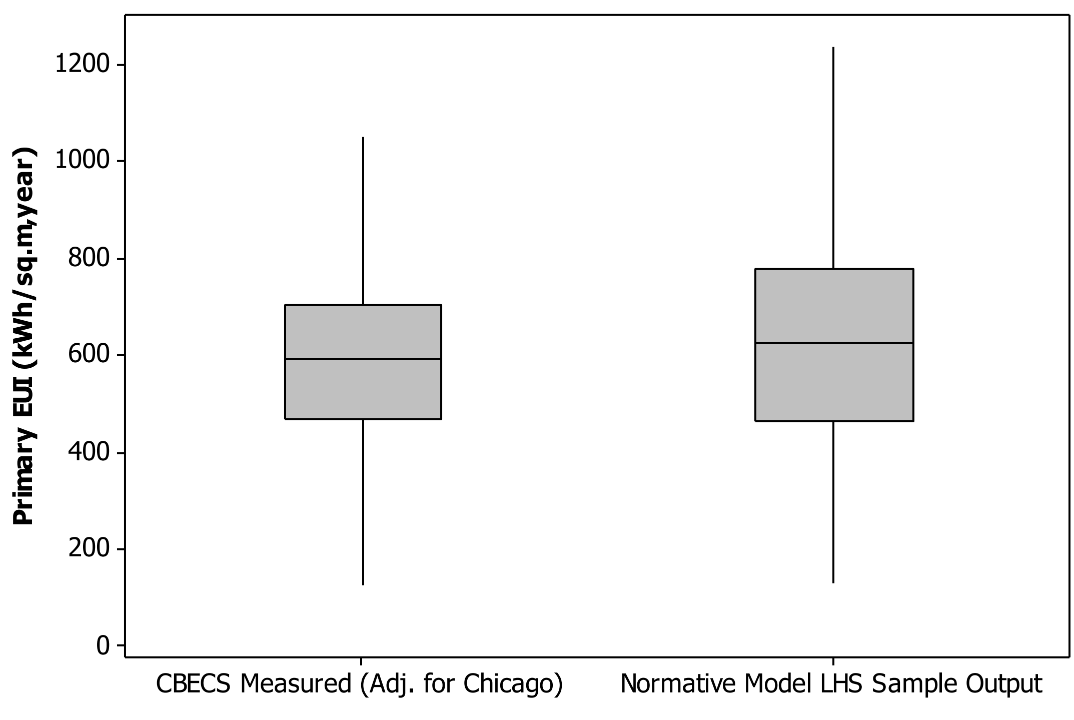


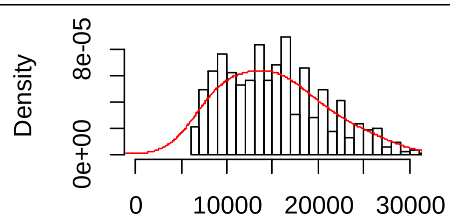
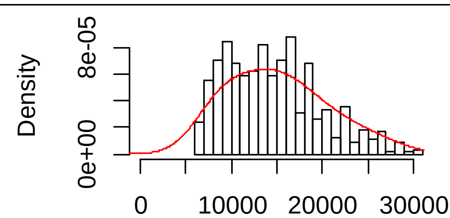
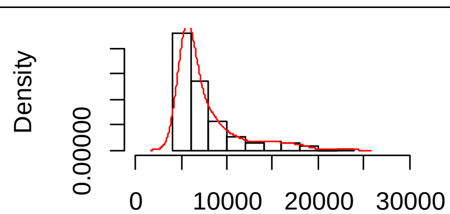
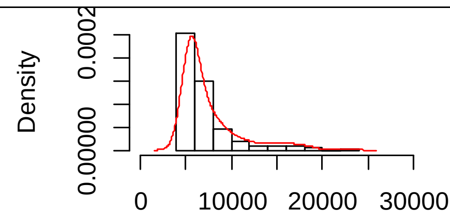
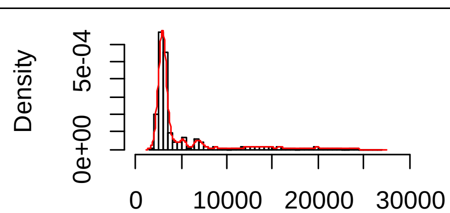
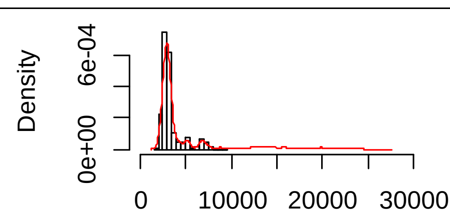
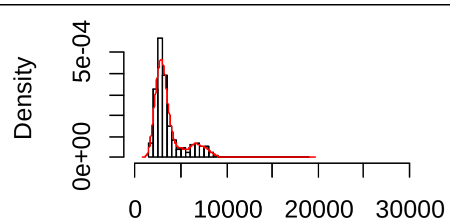
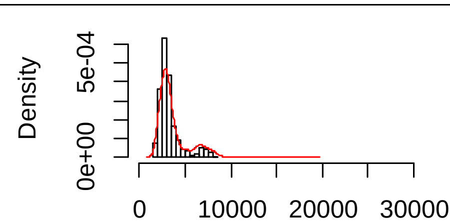
Figure 25 Ranges of primary EUI from the CBECS adjusted dataset and LHS of the normative model

By comparing the distribution of these measured data and the distribution of LHS sampled data from the normative model, we noticed that measured data have longer tails on the lower side, which contain a small portion of data outside the feasible range of the regression model. These data samples have to be manually removed to ensure that the inversion sampling always having results. In this test case, all samples smaller than 128.5 from the measured data set have been removed in the analysis. This process reduces the number of samples from 765 to 752. We found that this is indeed a common problem of using building energy model space to match the data space. The discrepancy between the lower bound of these two ranges may be caused by several possible reasons. From the data space side, errors exist in the estimation of gross floor areas, assumptions of fuel types, conversion of delivered energy to primary energy, and collection of delivered energy consumption data on site. From the model space side, errors also exist in specification of model input parameters, simplification of physical phenomenon, and assumptions of building scenario of use. Quantification of the abovementioned errors and distinguishing them from the inverse problem results deserves future work.

To use MCMC for Bayesian inference, the sample generated during a run of the algorithm should adequately (yet efficiently) represent the posterior distribution of interest. Before applying the MCMC method to solving the inverse problem, there are a number of important decisions to be made. The first decision is where to start the Markov chain sampling. In this study, since the mode values of variable ranges are very likely good values existing in the building stock, they are used as the start point. The second decision is how many iterations are needed. Inadequate number of iterations limits the sample range near the initial point, and may not reach the entire feasible range.

Raftery and Lewis (1995) suggested that the simulation may need a minimum number of 15,000 iterations to reach the extremes for heavy-tailed distributions. In this study, a simple convergence test has been performed for different iteration numbers from 15,000 to 30,000. The comparison for the parameter with widest spread and heaviest tails, gross floor area, is shown in Table 10. The comparison indicates that the PDF of gross floor area has stabilized after 25,000 iterations. The other parameters have been observed to become stable after 25,000 or even less iterations. Thus, this study samples 25,000 iterations in MCMC to solve the inverse problem.

Table 10 MCMC estimation of building gross floor area with different No. of iterations and burn-in length

No. of Iterations (n)	**Burn-in Length = 0**	**Burn-in Length = n/10**
5000		
15000		
20000		
25000		

The third decision is how many initial iterations should be discarded as "burn-in" samples. In a Markov chain process, the "burn-in" eliminates the initial random samples where the Markov chain has not stabilized. However, a good alternative to burn-in is to start from a point that "you don't mind having a sample" (Geyer, 2003a). In this study, a comparison of outcomes with and without burn-in samples under different number of iterations has been performed. The result is shown in Table 10. The result proves the principle Geyer (2003a) proposed. Thus, we do not apply burn-in samples.

The last two decisions could be considered is the spacing between iterations retained from the final analysis, and the number of chains/runs. Literature (Geyer, 2003b; Meersche et al., 2009) suggest that they are not sensitive to the simulation results, so that this study uses every sample from only one long chain.

3.4.4 Results

Using parameters quantified above, PDFs of the ten parameters are estimated and plotted in Figure 26.

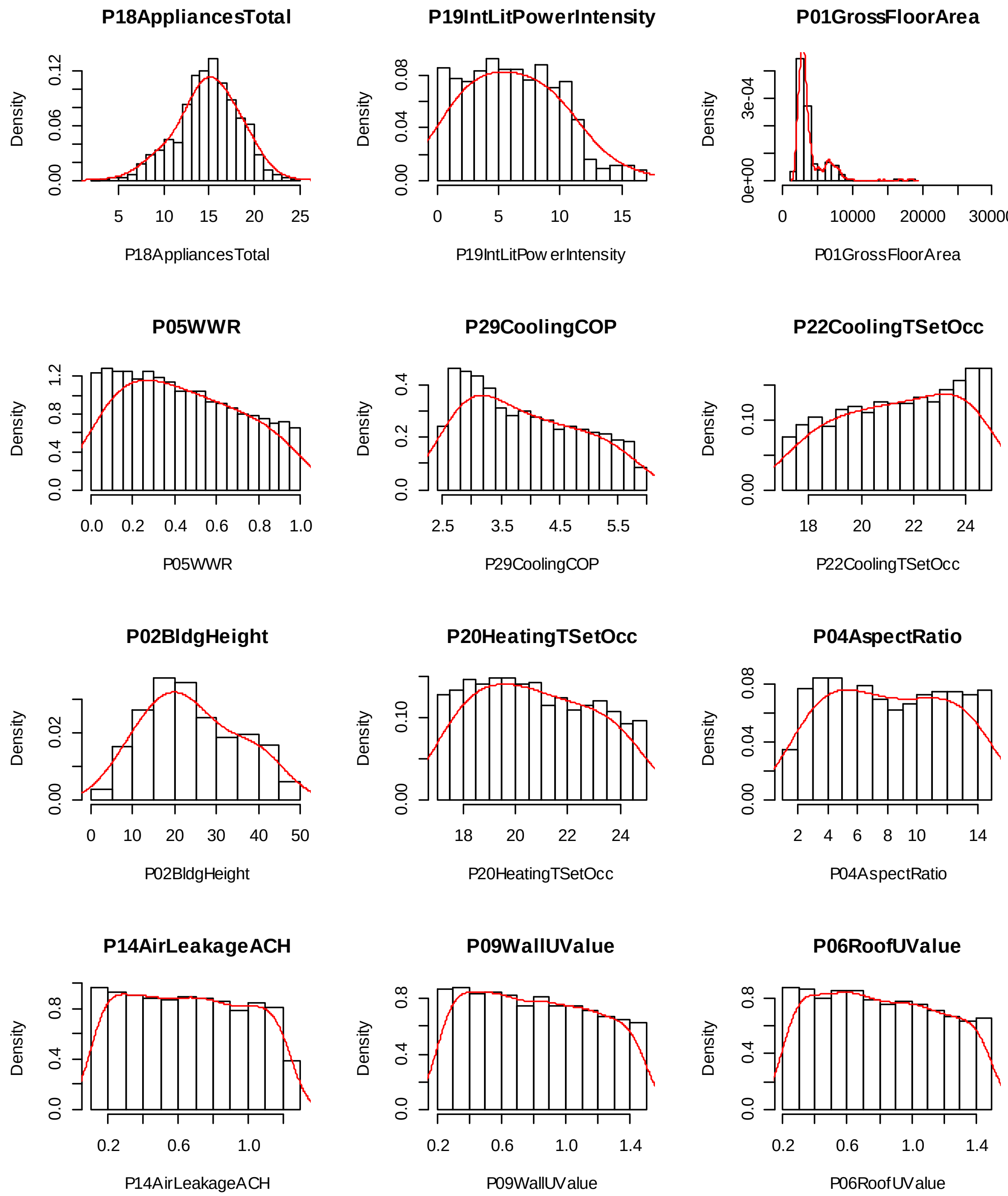


Figure 26 Histograms of estimated model parameters

To cross-validate the inverse problem results, we first directly compare the posterior PDF of the estimated gross floor area with measured data in CBECS 2003. Histograms of the two distributions are plotted in Figure 27. As presented in the result, the predicted distribution approximately replicates the actual distribution from CBECS 2003. However, this replication reduces the standard deviation of the dataset. As a result, a two-sample K-S test concludes that the two underlying distributions are significantly different.

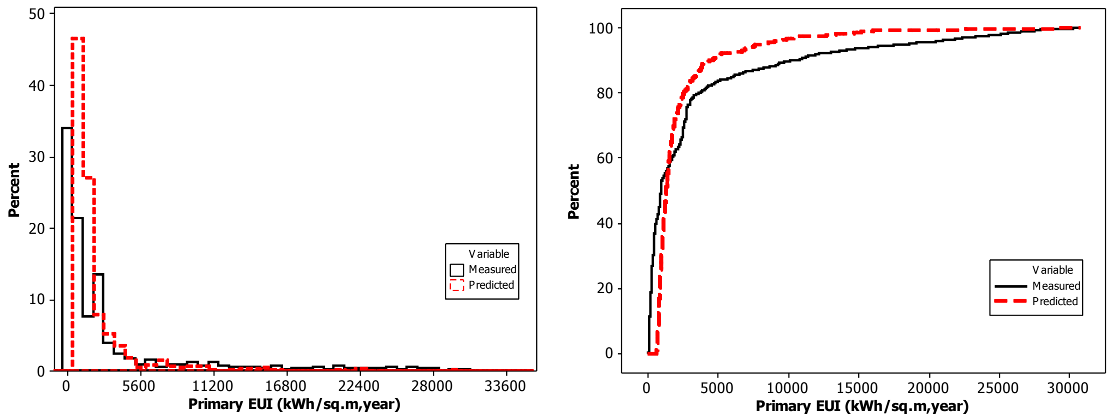


Figure 27 Histograms and CDFs of measured and predicted gross floor area

We also validate the inverse problem results by comparing the distributions of primary EUI. Primary EUI values of the CBECS 2003 office buildings (765 samples, adjusted for Chicago's climate) are chosen as the "Measured" dataset. In addition, we randomly draw 765 samples from the posterior distributions of model parameters and feed them to the linear regression model to generate another set of primary EUI values, named as "Inverse-Predicted". As shown in Figure 28, histograms of two datasets are approximately identical. A two-sample K-S test suggests that there is not sufficient evidence to conclude that the underlying distributions are significantly different, with a K-S test statistic of 0.064. Meanwhile, we also noticed that the histogram of the "Measured" dataset has longer tail near the lower bound. This issue, as discussed early in this section, is due to model assumptions and unknown errors in the measurement and modeling process.

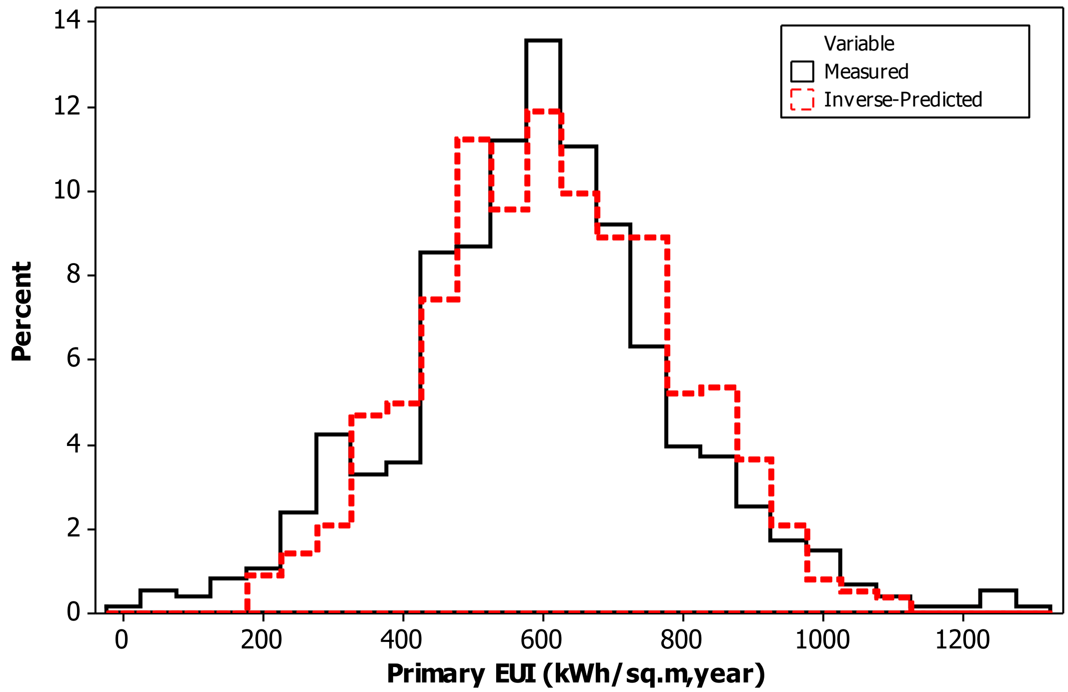


Figure 28 Histograms of measured and inverse-predicted primary EUI

It is worth noting that the estimated model parameter distributions in Figure 26 are not necessary the real-world distributions. Although they are very likely to be close to reality, they are estimated parameters that are derived by measurement data and the normative model. There exist errors between the data space and the model space that are not negligible. However, although the estimated PDFs may not be same as the real world, they can be used as an instrument to analyze the real world via interventions. This is further discussed in the concluding remarks of this chapter.

3.4.5 Findings of This Section

This section has successfully implemented an inverse problem solving framework. This framework is proven to be able to replicate the building stock by estimating posterior distributions of model parameters. These models are proven to be capable of replicating the building stock energy consumption distribution from measurement data. Therefore, Hypothesis 3C is proven to be eligible in the scope of this work.

3.5 Concluding Remarks

This chapter proposes an approach to replicate a building stock using its energy use consumption survey data. This approach first derives building energy use distribution of a specific location using larger scale building energy survey data. It then uses the derived energy use distribution to estimate the design and operational parameter distributions of a type of buildings across the building stock in the city.

This statistical method used to solve the inverse problem has advantages in both scalability and flexibility. First, this method provides the most possible distributions of individual building parameters without massively simulating hundreds of thousands of buildings in the building stock. The resulting parameter distributions can then be used to populate the building stock in any scale. Second, this method can flexibly adapt changes to the input parameter ranges and energy use data, and even the change of the target city, by simply updating the model parameters.

However, this statistical method is based on a series of assumptions and limitations. The first area of limitation comes from the statistical models. Every step of this approach, from climate adjustment to normative model regression to inverse sampling, has errors that we have to accept. These statistical errors are cumulated in the variance of the final results which bring risk to the decision maker. Better regression and sampling techniques, trained by better data, will reduce these statistical errors. The second area of limitation comes from the physical model. In the normative building energy model, building heat balance is simplified based on normative design practice that could be different from the actual situation. Further verification of physical model assumptions is desired. The third area of limitations comes from the matching of statistical model and the physical model. This approach ignores the difference (error) between data space and model space by using *measured* data to inverse-solve *modeled* parameters. Therefore, the estimated building parameter distributions should *not* be considered as the real world, but the "best guess" of the real world that will produce the same outcome of the real world. This "best guess" can be further improved by quantifying the measurement error between the data space and the model space using more measurement data.

The scale of the analysis deserves future research. In this chapter, we apply the approach to the city scale, which can be consisted of 100s or 1,000s of office buildings. For the scale of a district or a campus (with 10s of buildings) where aggregated utility data are available, we hypothesize that this approach can also be used to estimate building design and operational parameters. However, how to select the regression model, parameter ranges, and how to use the utility data still needs to be future studied.

Considering a larger scale of simulation which involves hundreds of building stocks in various cities, for example all commercial buildings in the state of Illinois, the proposed statistical approach is still computationally intensive to perform a long term intervention analysis. The model requires thousands of LHS samples to derive the regression model for each city, and tens of thousands of MCMC iterations to derive every model parameter distribution. The next chapter will propose a simpler method that is suitable for this scale of analysis. Both methods will also be compared with the massive modeling of every individual building in the stock.

4 A PROTOTYPE-BASED BUILDING STOCK MODEL

4.1 Introduction

Chapter 3 has proposed a statistical approach to estimate the distributions of building design and operational parameters in a building stock. Given its limitations in computational power and data requirement, a more scalable approach of populating building stocks for intervention analysis is desired. This chapter proposes a new approach using prototypes to generate building stocks in a region. This prototype-based building stock model is compared with the statistical model proposed in Chapter 3. Both of these two models are compared with a third approach, which is massive modeling of every single building using normative building energy model. The underlying logic of the sections in Chapter 3 and 4 can be illustrated as Figure 31.

This chapter is organized as following. Section 4.2 proposes three key functional steps and their implementations in this prototype-based building stock modeling approach. Section 4.3 evaluates the accuracy of this approach by comparing its predicted impact of two types of interventions with the predicted results from another two models: the statistical model and massive models. Based on the evaluation findings, Section 4.4 proposes a framework for the prototype-based building stock model. In the end, Section 4.5 concludes.

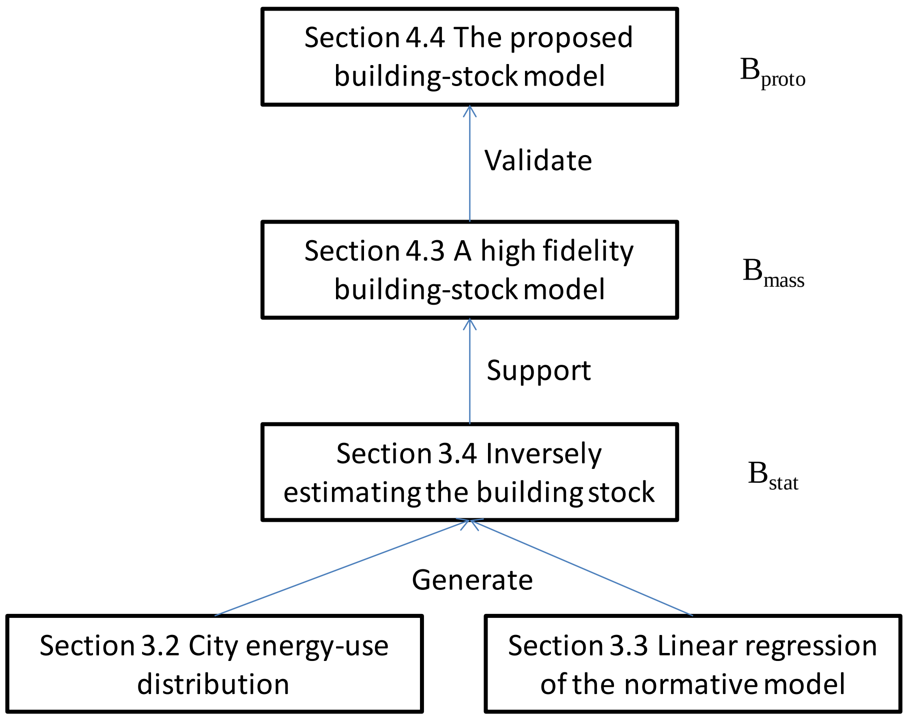


Figure 29 Organization of sections in Chapter 3 and 4

4.2 Key Functions of the Building Stock Model

A bottom-up building stock model has to be constructed based on a set of physically sense-making components, an efficient approach to scale up to the level needed, and a reasonably accurate method to evaluate decision alternatives to improve the building stock. These three desires can be formulated as three key functions of the proposed building stock model. First, this model is consisted of a set of subcomponents (i.e., the prototypical buildings) that *represent* the design and operational characteristics of typical commercial buildings in the place of interest. These prototypical building energy models should reflect the diversity of building location, form, materiality, HVAC, and equipment that are defined as inputs for the building energy calculator introduced previously. Meanwhile, this study proposes a method to *aggregate* these building energy models to estimate the energy consumption of building stocks without simulating every building in the stock. Ultimately, one could *intervene* the building stock by modifying the representation model parameters to predict the impacts. Figure 30 illustrates these three functions.

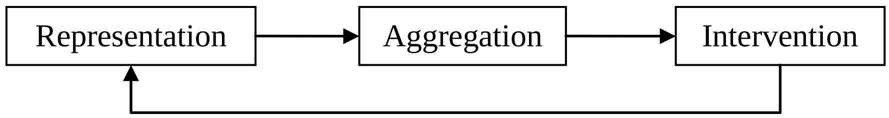


Figure 30 Three key functions of a building stock model

4.2.1 Representation

Prototype buildings, also called archetype buildings, are a set of universal models upon which other buildings are copied, patterned, or emulated. Generation of prototypal buildings is a data-intensive clustering process that requires data from regional energy survey data, building design standards/codes, and other statistical information. This technique has been implemented to countries such as Japan (Yohei Yamaguchi et al., 2007), Canada (Parekh, 2005), and United Kingdom (Clarke et al., 2004; Ruchi, 2012) for both residential and commercial buildings. In the United States, the most referenced is from LBNL who developed a series of prototypical buildings over several years. Huang et al. (1991) and Huang and Franconi (1999) presented extensive summaries of work in this area. Huang et al. (2005) later also presented an analysis of 1,999 building data to derive prototypical buildings in the U.S. Three recent efforts to develop prototypical energy models of buildings include a set of standardized energy simulation models for commercial buildings from the University of Massachusetts (Stocki et al., 2007), an assessment of the entire commercial building sector by NREL (Griffith et al., 2007), and a residential building benchmark model from the DOE Building America program (Hendron, 2008). These studies are foundations of the current commercial reference buildings (Deru et al., 2011) in the U.S.

In the commercial reference buildings, models of different building design and operational specifications are developed for 16 building types, three age vintages (new, post-1980, and pre-1980), and 16 cities in different climate zones. These models are all specified as detailed input files for dynamic simulation tools such as DOE-2 and EnergyPlus. Meanwhile, they are not intended to represent energy use in any particular building. Rather, they are hypothetical models with pre-determined operations that meet certain minimum requirements. To use these models to generate useful information, people have to run thousands of models to cover all the conditions in the nation. Considering the complexity of every single model, this massive simulation project can only be done by developing automated software and using super computers. Several recent projects were conducted by NREL (Griffith et al., 2007, 2008) and PNNL (J. Zhang et al., 2010).

This study will work from the existing set of commercial reference buildings mentioned above and published U.S. Department of Energy (DOE) (2009), select a sub-set of input parameters for each instance, and develop the same set of models for the normative building energy model. These 16 building types, 16 climate zones, and 3 vintages together provide a combination of 768 prototypes for commercial buildings in the U.S., listed in Table 11. These buildings cover more than 80% of the total energy consumption of commercial buildings in the United States, according to the CBECS 2003 database.

Table 11 List of 16 building type considered in this thesis

Building Types	Climate Zones	Building Age Vintages
▪ Large Office ▪ Medium Office ▪ Small Office ▪ Warehouse ▪ Stand-alone Retail ▪ Strip Mall ▪ Primary School ▪ Secondary School ▪ Supermarket ▪ Quick Service Restaurant ▪ Full Service Restaurant ▪ Hospital ▪ Outpatient Health Care ▪ Small Hotel ▪ Large Hotel ▪ Midrise Apartment	▪ 1A – Miami, FL ▪ 2A – Houston, TX ▪ 2B – Phoenix, AZ ▪ 3A – Atlanta, GA ▪ 3B-Coast – Los Angeles, CA ▪ 3B – Las Vegas, NV ▪ 3C – San Francisco, CA ▪ 4A – Baltimore, MD ▪ 4B – Albuquerque, NM ▪ 4C – Seattle, WA ▪ 5A – Chicago, IL ▪ 5B – Boulder, CO ▪ 6A – Minneapolis, MN ▪ 6B – Helena, MT ▪ 7 – Duluth, MN ▪ 8 – Fairbanks, AK	▪ New New constructions in 2004 ▪ Post-1980 Existing buildings constructed in or after 1980 ▪ Pre-1980 Existing buildings constructed before 1980

In applications, this list of building types is neither sufficient nor necessary to be used for all the places. The rest of building types in the literature have different energy consumption patterns and cannot be modeled simply. Because of their small share in the national electricity consumption, they are ignored in this study. Indeed, a subset of buildings in this list can still form a reasonable abstraction of reality.

4.2.2 Aggregation

Aggregation of building energy consumption exists in many aspects of this study. Aggregation of building energy models on the national level typically uses weighting factors to scale up the energy use of individual prototypical buildings. Because real building statistical data are insufficient, it is difficult to develop reasonable weighting factors for the national level and almost impossible for state or smaller levels (Deru et al., 2011). (Jarnagin & Bandyopadhyay, 2010) analyzed the McGraw-Hill (McGraw Hill, 2011) database from 2003 to 2007 to develop weighting factors for the *new construction* reference buildings. However, weighting factors for *existing* buildings have never been developed in the U.S.

Aggregation of building energy models on the state or city level recently benefits from the development of Geographic Information System (GIS). Geographic information research and technologies have experienced over four decades of development, from the mainframe to the workstation to the desktop, and the latest laptop and mobile devices. (Jiang & Yao, 2010) states that current GIS technologies have collected massive data for the research areas of (1) capturing individual-based data for urban structure and dynamics analysis, (2) modeling urban complexity and hierarchy, (3) simulating urban transportation systems, and (4) analyzing urban growth, changes, and impacts. Several recent studies (Meinel, Hecht, & Herold, 2009; Tanikawa & Hashimoto, 2009) use urban GIS data to explore the impact of urban built form and evolution to the demand of heating energy and construction material at urban scale. The development of GIS databases enables another way of aggregation, which is to scale energy use up by actual building floor areas in the city.

This study uses the second aggregation approach mentioned above. This approach considers a cluster of buildings of the same type (use the same prototypical model) within the same region (use the same weather data) to be one stock. This aggregation process can be express as:

$$E_i^{(stock)} = w_i^{(proto)} E_i^{(proto)} \tag{4-1}$$

where $E_i^{(stock)}$ is the total energy performance indicator (can be thermal needs, delivered energy, primary energy, or CO_2 emissions) of the building stock i; $E_i^{(proto)}$ the energy consumption of the prototype of one type of buildings, with $w_i^{(proto)}$ the scaling factor that quantifies the number of similar buildings with that prototype. The total energy performance indicator of that region, consisted of multiple stocks, can be calculated as the aggregation of the stocks:

$$E^{(region)} = \sum_i E_i^{(stock)} \tag{4-2}$$

Figure 31 is a schematic illustration of this two-step aggregation process.

Figure 31 The concept of building aggregation

4.2.3 Intervention

Simulation models are expected to predict and recreate visible phenomena that are not normally (or easily) observable in the physical world. An intervention analysis to a mathematical model is the process of evaluating impacts from modifications to a set of model input parameters. Interventions to building energy models can be used to estimate the outcomes of applying energy efficiency measures and demand response scenarios.

Energy efficiency measures and demand response scenarios for buildings have often been analyzed in case studies involving a specific building. Such an approach makes it difficult to generalize the conclusions and implications out of the study. For large scale building stock modeling, people are usually more interested in the contributions of interventions to the overall regional performance, such as primary energy consumption, CO_2 emission, peak load, etc. Previous studies have developed methodology to quantify the impact of incorporating interventions to buildings up to the municipal level (Clarke et al., 2004; Huang et al., 1991; Jones, Lannon, & Williams, 2001; Y. Yamaguchi, Fujii, Morikawa, & Mizuno, 2004).

In general, an intervention to a building stock model can be expressed as

$$X'_{i,j} = f_j(X_{i,j}) \, , \qquad \textit{(4-3)}$$

where f_j is the intervention function that modifies the parameter j of building stock i.

4.3 Evaluation of the Proposed Approach

Hypothesis 4A: Estimating energy efficiency interventions at the whole building stock level does not require massive simulation of individual buildings in the stock. Instead, prototypical buildings could sufficiently predict the intervention effects such as performance degradation, energy retrofit, and demand response.

The major hypothesis being evaluated in this chapter can be described as Hypothesis 4A. As proposed by Judkoff, Wortman, and Burch (1983), there are typically three ways to evaluate the accuracy of a building energy model:

• *Empirical Validation*—in which calculated results from a program, subroutine, algorithm, or software object are compared to monitored data from a real building, test cell, or laboratory experiment.

• *Analytical Verification*—in which outputs from a program, subroutine, algorithm, or software object are compared to results from a known analytical solution or a generally accepted numerical method for isolated heat transfer under very simple, highly constrained boundary conditions.

• *Comparative Testing*—in which a program is compared to itself or to other programs.

Table 12 Building energy model validation techniques (Judkoff, 1988)

Technique	Advantages	Disadvantages
Empirical Validation: Test of model and solution process	• Approximate truth standard within experimental accuracy • Any level of complexity	• Experimental uncertainties • High expense in time and money • Only a limited number of test conditions are practical
Analytical Verification: Test of solution process	• No input uncertainty • Exact mathematical truth standard for the given model • Inexpensive	• No test of model validation • Limited to highly constrained cases for which analytical solutions can be derived
Comparative Testing: Relative test of model and solution process	• No input uncertainty • Any level of complexity • Many diagnostic comparisons possible • Inexpensive and quick	• No absolute truth standard (only statistically based acceptance ranges are possible)

In this study, we follow the third validation technique in Table 12 and compare outcomes of three building stock models under the same test scenarios. Three almost identical building stocks generated by three simulation models respectively are compared under the same intervention scenarios. The first one is generated by prototypical buildings and weighting factors, denoted as $\mathcal{B}_{proto}$. The second one is generated by the statistical model proposed in Chapter 3, denoted as $\mathcal{B}_{stat}$. The third one, of which every individual building simulated by the normative building energy model introduced in Chapter 2, is denoted as $\mathcal{B}_{mass}$.

According to the process of model generation and the number of building samples being simulated, the prototype-based model is the most flexible one yet requires the least computational power. The massive model, although is considered to be the most accurate approach to represent a set of individual buildings, requires the most computational power and therefore is the least flexible model to predict the impact of interventions. Table 13 summarizes the comparison of three models.

Table 13 Three building stock models being compared

Model	$\mathcal{B}_{proto}$	$\mathcal{B}_{stat}$	$\mathcal{B}_{mass}$
Definition	Prototype-based	Statistical	Massive
Required computation power	Least	Medium	Most
Flexibility in Changes	Most	Medium	Least

To evaluate these three models, we first adjusted their sizes to have the identical baseline primary energy consumption, and then applied to two intervention scenarios: (1) performance degradation and (2) energy retrofit and demand response. Intervention outcomes of the massive simulated stock $\mathcal{B}_{mass}$ is considered to be the accurate solution, and are compared with results from $\mathcal{B}_{proto}$ and $\mathcal{B}_{stat}$.

4.3.1 Baseline Setup

To evaluate two models, we create a city that is consisted of only office buildings in three different sizes and vintages. The fraction of each category, expressed as weighting factors, is based on the weighting factors of new construction buildings derived by Jarnagin and Bandyopadhyay (2010) based on the McGraw Hill database from 2003 to 2007. These weighting factors are available online (DOE, 2009) and adapted by the US DOE commercial reference buildings. However, weighting factors for buildings constructed before 2004 have not been developed, because adequate data about the existing building stock have not been identified (Deru et al., 2011). In this study, we assume that weighting factors for all building vintages are identical. This is only an assumption for the purpose of comparing two modeling approaches rather than a prediction of the building stock composition. These weighting factors are listed in Table 14.

Table 14 Weighting factors used for the prototypical offices in different vintages and sizes in Chicago

	Post-2004 (DOE, 2009)	1980-2004[4]	Pre-1980
Small Office	2213.0	2213.0	2213.0
Medium Office	261.4	261.4	261.4
Large Office	11.7	11.7	11.7

To generate building stock $\mathcal{B}_{proto}$, we first use these weighting factors to scale up the floor area of nine prototypical office buildings for Chicago, following the process described in Equation (4-1):

$$E_{primary}^{(region)} = \sum_{i=1}^{9} w_i^{(proto)} E_{primary,i}^{(proto)} \tag{4-4}$$

where $E_{primary}^{(proto)}$ is the total primary energy consumption of stock $\mathcal{B}_{proto}$ and $E_{primary,i}^{(proto)}$ the primary energy consumption of the prototypical building of building stock i from Table 14.

To generate building stock $\mathcal{B}_{stat}$, we continuously sample the PDFs of model parameters in Figure 26 until the objective $E_{primary}^{(stat)} \geq E_{primary}^{(proto)}$ is just satisfied. The

[4] Scaling factors for buildings built before 2004 have not been developed in the US. This test assumes that they are identical to new construction. This is only an assumption for the purpose of comparing two modeling approaches rather than a prediction of the stock composition.

derived model parameter samples are then fed into the regression model to calculate the corresponding energy consumption outcomes.

To generate building stock $\mathcal{B}_{mass}$, feed all derived model parameters samples from the previous step to a whole building energy simulation tool, in this case the normative building energy model, to calculate the corresponding energy consumption outcomes. The process of generating three building stocks is illustrated as a flow chart in Figure 32.

According to the abovementioned methods, two baseline building stocks are set up for the evaluation. Their initial primary energy consumptions (in MWh/year), total number of buildings, and total gross floor area are listed in **Error! Reference source not ound.**. It is worth mentioning that these two building stocks have almost identical primary energy consumptions, but different individual buildings that construct them. This is because $\mathcal{B}_{stat}$ is statistically constructed based on energy consumption data, whereas $\mathcal{B}_{proto}$ is conceptually constructed based on minimum design standards.

Table 15 Description of building stocks generated by three models

	$\mathcal{B}_{proto}$	$\mathcal{B}_{stat}$	$\mathcal{B}_{mass}$
Primary energy consumption (MWh/year)	4,476,918	4,477,797	5,190,915
Number of buildings	7,458	2,028	2,028
Total gross floor area (1000 m^2)	8,926	7,570	7,570
Primary EUI (kWh/m^2,year)	502	592	686

Evaluation of the statistical and the prototype-based models has been implemented in R (R Development Core Team, 2008) and CoBAM (developed in collaboration with Argonne National Laboratory, introduced in Chapter 6), respectively. The massive models have been implemented in Phoenix Model Center (Phoenix Integration Inc., 2012) using the parameters derived by R.

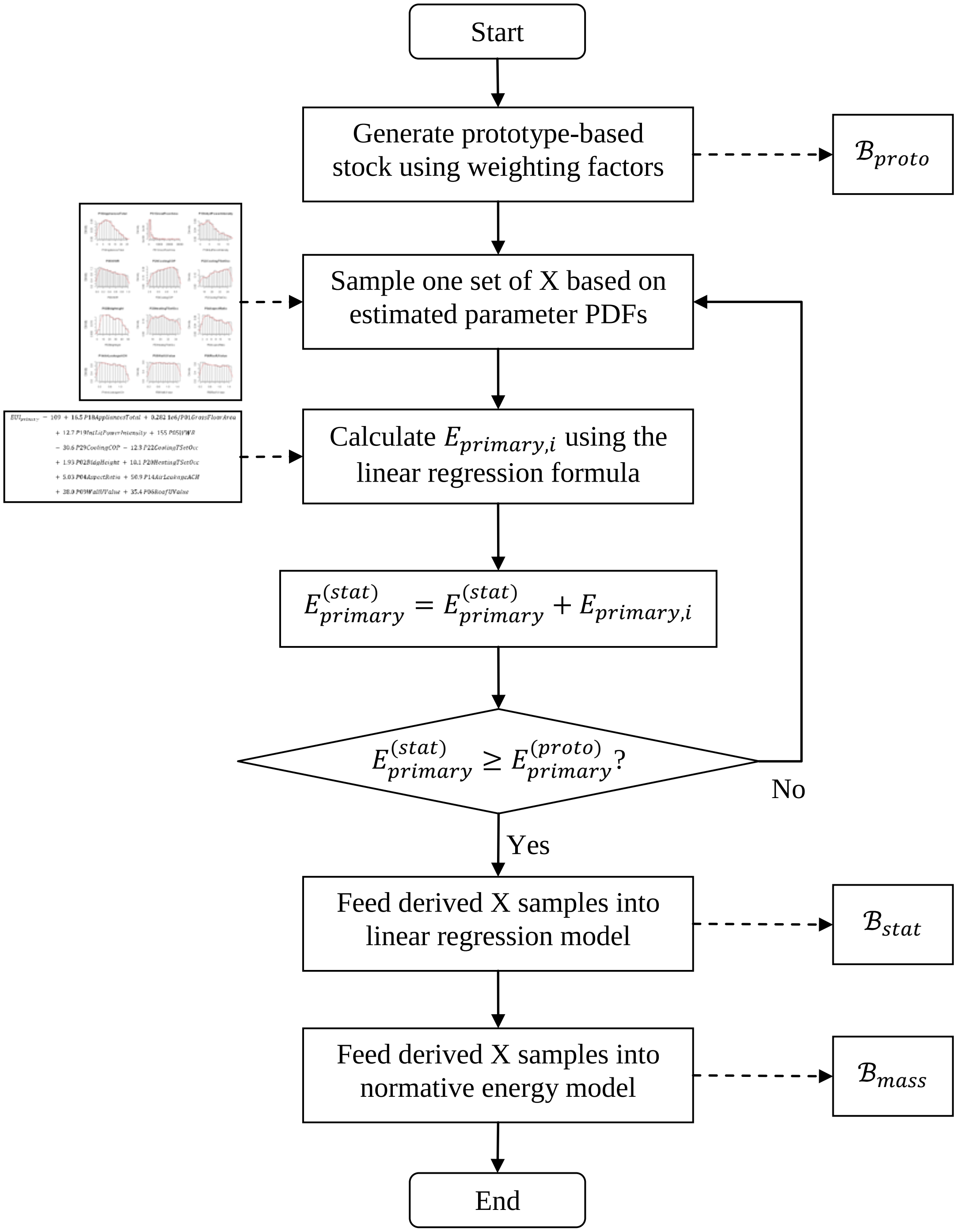


Figure 32 Sampling process to generate comparable building stocks to evaluate three modeling techniques

4.3.2 Evaluation Scenario 1: Performance Degradation

Energy inefficiency grows over the building lifecycle (Brown, Kreitler, & Wolfe, 1996). These inefficiencies can result from degradation of materials and equipments, change in use, and/or unexpected faults (Heo, 2011). Building performance degradation process can be captured with, and defined as, the annual degradation ratio (ADR), proposed by Zhao, Martinez-Moyano, and Augenbroe (2011). The building energy performance decreases by applying a set of degradation factors to the input parameters. For a degrading building parameter j of building i, its value at year $(t+1)$, denoted as $X_{i,j}^{(t+1)}$, is

$$X_{i,j}^{(t+1)} = (1 + ADR_j)X_{i,j}^{(t)} . \qquad (4\text{-}5)$$

According to this degradation function, the performance of each building component consistently degrades every year until system maintenance is performed to that component. In this scenario, ADR values are applied to their corresponding building model parameters of both models to check the difference in outputs (e.g., total primary energy consumption) from two models.

More specifically, two building model parameters are considered to degrade annually: (1) energy use intensity of appliances (P18AppliancesTotal, unit: W/m^2), (2) energy use intensity of the lighting system (P19IntLitPowerIntensity, unit: W/m^2), and (3) the cooling system COP (P29CoolingCOP, unit: kW/kW). In reality, the ADR values vary by case and have relatively significant impacts to the projection of building energy efficiency levels. Thus, multiple scenarios of degradation shall be considered when applying this model to compare policy making decision options. In this test, we apply relatively high ADR values to test the extreme conditions: ADR_{P18} = 0.10, ADR_{P19}

= 0.10, and ADR_{P29} = −0.10 (shown in Table 16). Using these values means that the power intensity of appliances and lighting fixtures increases by 10% annually, and the performance of the cooling system decreases by 10% annually.

Table 16 ADR values applied in Scenario 1: Performance Degradation

Model Parameter	Unit	ADR_j
P18AppliancesTotal	W/m^2	0.10
P19IntLitPowerIntensity	W/m^2	0.10
P29CoolingCOP	kW/kW	-0.10

Figure 33 depicts the increase of appliances power intensity over 20 years (the other parameters are steady) and the resulting building stock primary energy consumption increase predicted by three models. In this test, the value (mean value for the statistical and massive models) of parameter P18AppliancesTotal has increased significantly, from 14.9 to 100.2 W/m^2. Such an intervention brings the energy consumption of three building stocks significantly by relatively similar percentages, of which the statistical model has the highest final consumption value: 340% of its baseline value. However, we notice the trend that the trajectory predicted by the statistical model starts to increase much faster than the other two. This will yield to a much bigger discrepancy between the statistical and the other two models for a larger or longer intervention.

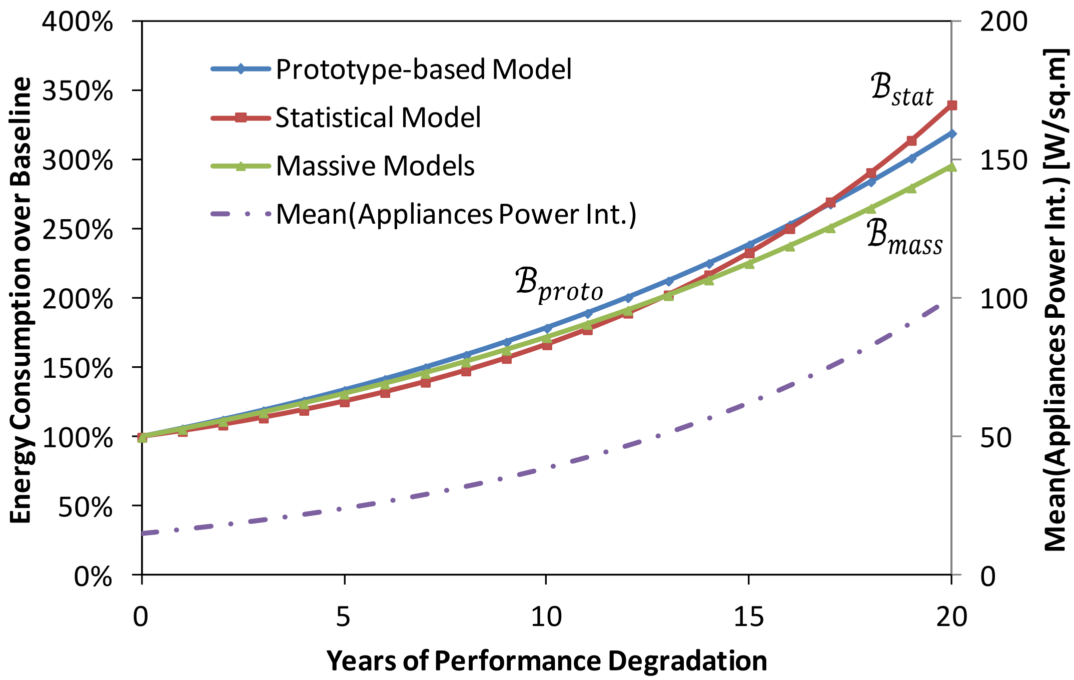


Figure 33 Impact of appliances performance degradation predicted by three building Stock models

Figure 34 depicts the increase of lighting power intensity over 20 years (the other parameters are steady) and the resulting building stock primary energy consumption increase predicted by three models. In this test, the value (mean value for the statistical and massive models) of parameter P19IntLitPowerIntensity has increased significantly, from 6.3 to 42.1 W/m^2. Such an intervention brings the energy consumption of three building stocks significantly but by very different percentages. The energy consumption trajectory predicted by the statistical model has a final value as only 176% of its baseline, much lower than those from the other two models: approximately 300% of baseline. Figure 35 also depicts a significant discrepancy between the prediction from the statistical model and the ones from the other two models.

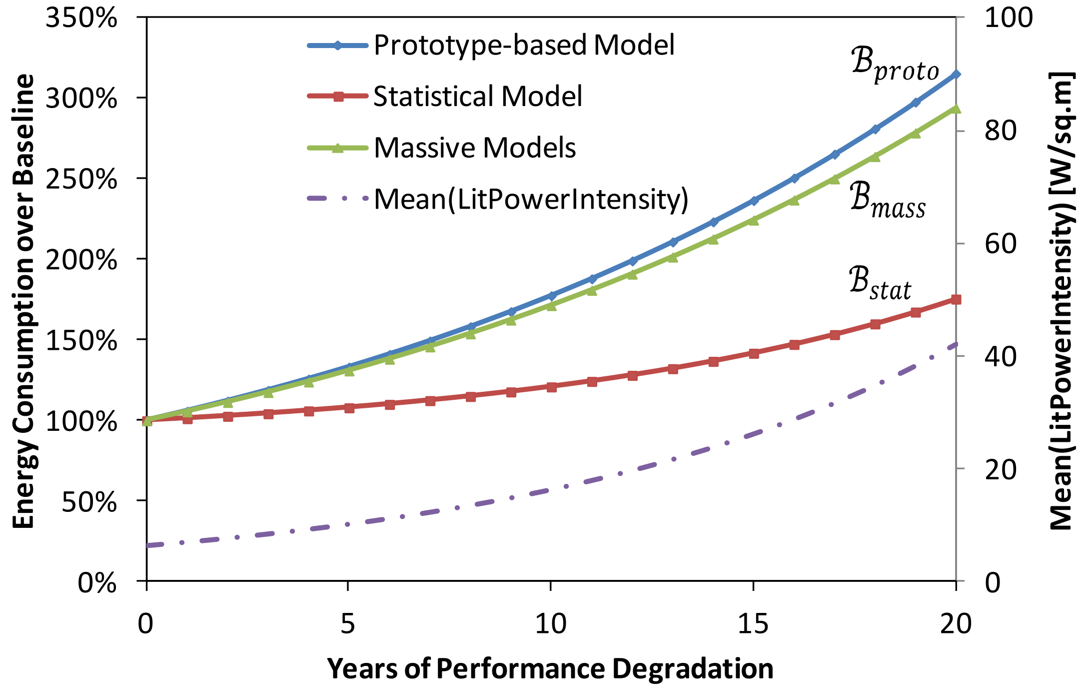


Figure 34 Impact of lighting performance degradation predicted by three building stock models

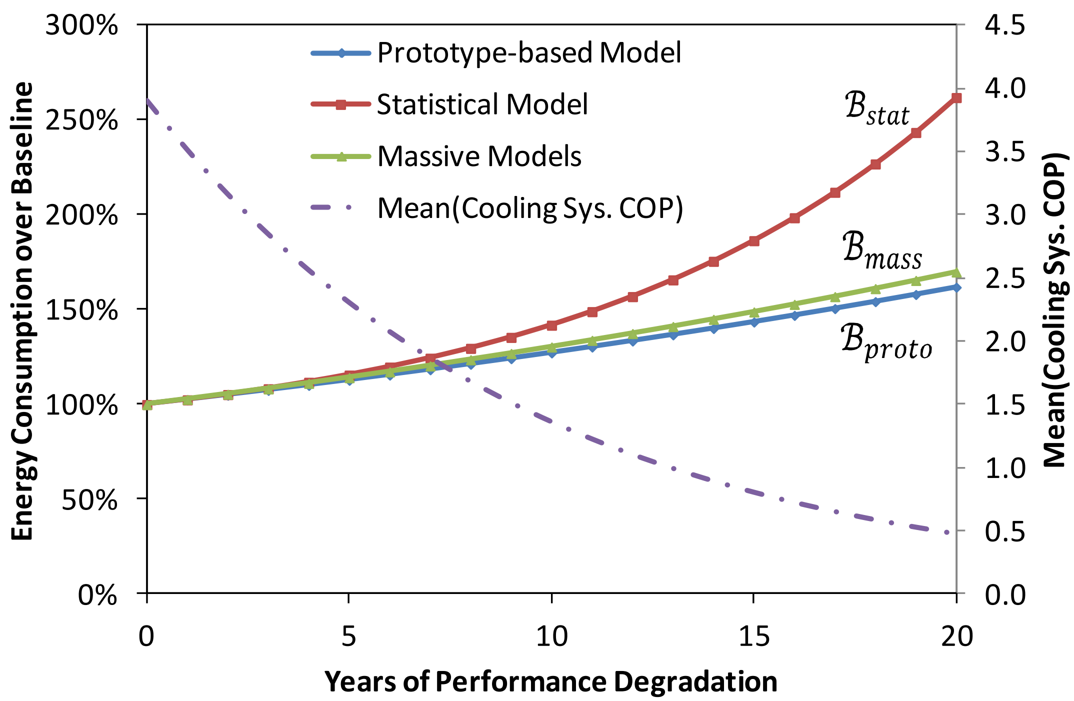


Figure 35 Impact of cooling system performance degradation predicted by three building stock models

Two evaluation criteria are used to quantify the discrepancy among three models: (1) predicted final energy increase percentage from baseline and (2) percentage higher than the massive model result. Both criteria use the predicted value of year 20 to compared three models, listed in Table 17.

Table 17 Comparison of three models for performance degradation prediction

Intervention	Evaluation Criteria	$\mathcal{B}_{proto}$	$\mathcal{B}_{stat}$	$\mathcal{B}_{mass}$
Appliances	Predicted Energy Increase % from Baseline	220%	240%	196%
	% Higher than the Massive Model Result	8%	15%	0%
Lighting	Predicted Energy Increase % from Baseline	215%	76%	194%
	% Higher than the Massive Model Result	7%	-40%	0%
Cooling COP	Predicted Energy Increase % from Baseline	62%	162%	70%
	% Higher than the Massive Model Result	-5%	54%	0%

The comparison indicates that for the selected three intervention scenarios over 20 years of performance degradation, the difference between results from the prototype-based and the massive models is always within ±8%. This indicates that the prototype-based model can be used instead of massive modeling to predict the relative energy performance impacts to a building stock from system performance degradations. However, the statistical model predicts results ±54% different from the massive model.

4.3.3 Evaluation Scenario 2: Energy Retrofit and Demand Response

A building-stock model has to be capable of effectively predicting the relative energy savings of buildings after energy retrofit. Previous research studies have established a methodology to quantify the result of incorporating energy efficiency measures, or retrofit, into buildings at the scale of a building stock (Clarke et al., 2004; Huang et al., 1991; Jones et al., 2001; Y. Yamaguchi et al., 2004; Zhao et al., 2011). In addition, demand response behaviors of building stocks also change the value of building parameters over time. Theoretically, an energy retrofit or demand response intervention situated in the building energy model can be described as "When the system hits state i, change it to state j" (Y. Zhang, Augenbroe, & Vidakovic, 2005). A generic formula of the abovementioned interventions is

$$X_{i,j}^{(t+1)} = f_j\left[X_{i,j}^{(t)}\right], \quad (4\text{-}6)$$

where f_j is the intervention function that quantifies an update to a specific building parameter j. In this scenario, all non-geometry parameters in Equation (3-5) are chosen as retrofit parameters. Typical retrofit functions for these eight parameters are listed in Table 18.

Table 18 Retrofit functions applied in Scenario 2: Energy Retrofit and Demand Response

Intervention Type	**Model Parameter *X***	**Unit**	f_j
Appliances Upgrade, or Demand Response	P18AppliancesTotal	W/m2	$0.7X^{(t)}$
Lighting Fixtures Upgrade, or Demand Response	P19IntLitPowerIntensity	W/m2	$0.6X^{(t)}$
Chiller Retro-commissioning	P29CoolingCOP	kW/kW	$1.1X^{(t)}$
Demand Response: Increase Cooling Tset	P22CoolingTSetOcc	℃	$X^{(t)} + 2$
Demand Response: Decrease Heating Tset	P20HeatingTSetOcc	℃	$X^{(t)} - 2$
Infiltration Reduction	P14AirLeakageACH	ACH	$0.9\mathrm{X}^{(t)}$
Wall Insulation Addition: R15	P09WallUValue	W/m2,K	$\frac{1}{1/X^{(t)}+1/0.38}$
Roof Insulation Addition: R20	P06RoofUValue	W/m2,K	$\frac{1}{1/X^{(t)}+1/0.28}$

In this test, parameter interventions are applied individually to all three models to compare their prediction difference in primary energy reduction, quantified as percentage of the baseline consumption. Figure 36 shows the intervention outcome. In this figure, the relative primary energy reduction predicted by the massive model is set to be 100, and the relative reduction predicted by the other two models (based on their own baselines) are scaled according to the massive model. The comparison indicates in most interventions, that energy-saving percentages predicted by the prototype-based model are close to those by the massive model, with a standard deviation value 14.5% for the eight interventions. However, the statistical model yields a much higher discrepancy from the massive model predictions, with a standard deviation value 49.4%.

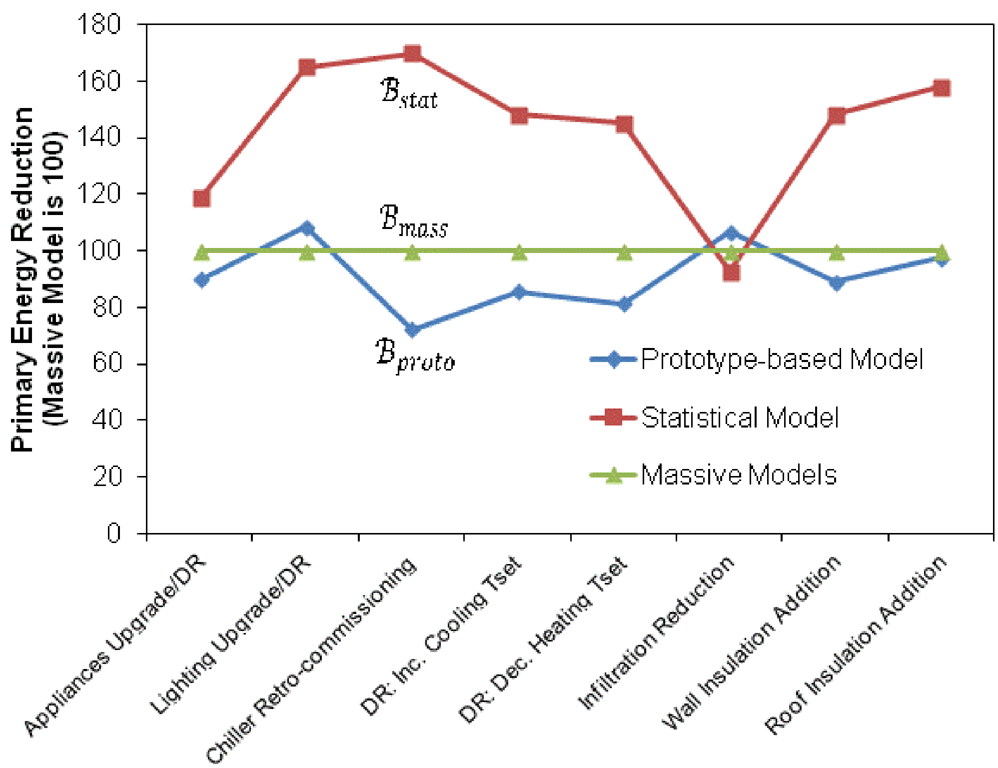


Figure 36 Impacts of parameter interventions predicted by three building stock models

4.3.4 Findings of the Evaluation

Comparison results in two scenarios have shown two major findings:

1) For long-term or huge interventions such as performance degradation, the prototype-based building stock model is robust enough and provides very close

predictions compared to massive models. However, the statistical model proposed in Chapter 3 yields to significant discrepancy.

2) For instant or slight interventions such as energy retrofit or demand response, both the prototype-based and statistical models can provide relatively close predictions compared to massive models, yet the prototype-based model is observed to be more accurate. Both models are also capable of predicting the order of impacts from interventions, so that both can be used to rank the effectiveness of interventions.

This higher discrepancy between the statistical model and other in performance degradation is very likely due to the reason that the underlying linear regression formula in the statistical model is only accurate for those input parameters within their typical ranges that were sampled to perform the regression analysis. This is not surprising because regression models are usually good for prediction via interpolation, but not extrapolation.

On the other hand, the small discrepancy between the prototype-based model and the massive modeling approach is very likely that the building energy model, at least the normative building energy model, is a fairly linear system. Changes to most of its input parameters are proportionally reflected in the change of outcomes.

4.4 The Framework of A Prototype-Based Building Stock Model

Given the feasibility approval of the prototype-based building-stock model, we hereby propose a framework of modeling building-stock energy performance using prototypical buildings. The proposed framework has four levels of analysis throughout the process of aggregation, from building thermal systems to the overall indices of building stocks. These four levels and the aggregations between them are illustrated as Figure 37.

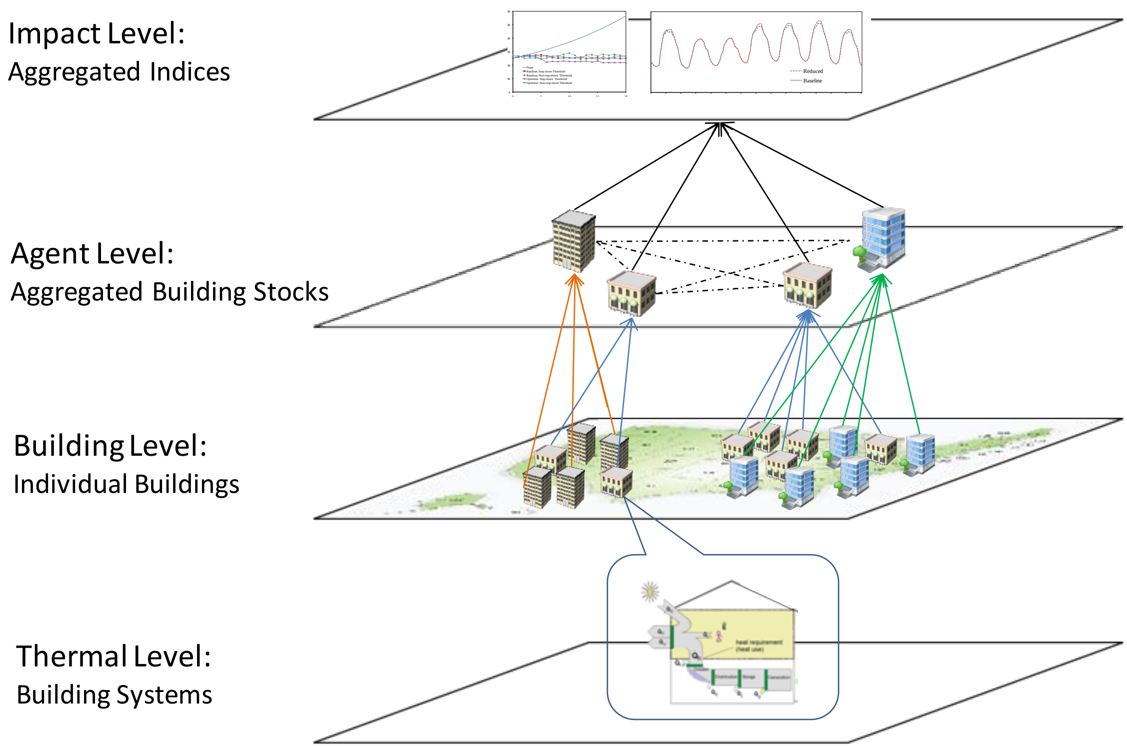


Figure 37 Schematic of a prototype-based building stock modeling framework

In this framework, a single-building energy calculator (Level 1) serves as the engine to solve energy flows amongst building systems. Above the building systems level, all individual buildings (Level 2) in the modeled area are aggregated as building stocks (Level 3). These building stocks, modeled as agents, are ultimately summed to estimate the regional energy consumption (Level 4).

This framework will be implemented and tested in Chapter 6 for energy retrofit analysis and Chapter 7 for demand response analysis, at two different temporal scales.

4.5 Concluding Remarks

This chapter proposes a prototype-based building stock model, and proves the hypothesis that this model is accurate and scalable to perform large-scale intervention analysis. In the evaluation of three models, the proposed prototype-based model has shown plausible agreement with the massive modeling approach, and much better predictions compared to the statistical model presented in Chapter 3. We gain confidence from this chapter and will apply as the foundation of this thesis research.

5 AGENT-BASED MODELING AND SIMULATION

5.1 Introduction

ABMS is a technique for bottom-up modeling, providing an alternative perspective to those that can be attained by using optimization or general-equilibrium approaches. In agent-based simulations, system behavior emerges from the behaviors of interacting agents. An agent is an autonomous and potentially self-directed entity that is characterized by a set of attributes. Agents are situated in a system in which they interact with each other and their environment. The behavior of an agent is usually driven by its goals. In achieving these goals, specific (i.e., predefined) rules guide the agents' performance when interacting with the other agents. An agent has the potential to learn based on environmental information as well. In other words, three updates may apply to agents in an ABMS: the situated update, the adaptive update, and the interactive update, illustrated as Figure 38.

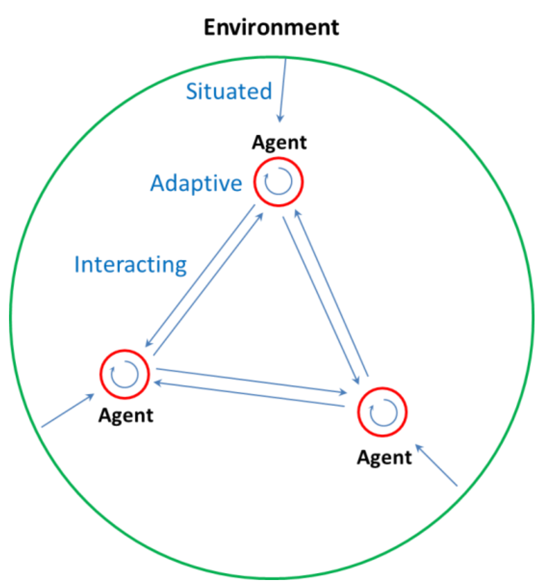


Figure 38 Conceptual illustration of three possible interactions in an ABMS

As described in (Macal & North, 2005), from a practical modeling standpoint, agents are considered to have the following characteristics:

1) An agent is identifiable, a discrete individual with a set of characteristics and rules governing its behaviors and decision-making capability. Agents are self-contained. The discreteness requirement implies that an agent has a boundary such that users can easily determine whether something is part of an agent, is not part of an agent, or is a shared characteristic.
2) An agent is autonomous and self-directed. An agent can function independently in its environment and in its dealings with other agents, at least over a limited range of situations that are of interest.
3) An agent is situated, living in an environment with which it interacts with other agents. Agents have protocols for interaction with other agents, such as for communication, and the capability to respond to the environment. Agents have the ability to recognize and distinguish the traits of other agents.
4) An agent may be goal directed, having goals to achieve (not necessarily objectives to maximize) with respect to its behaviors. This allows an agent to compare the outcome of its behavior relative to its goals.
5) An agent is flexible, having the ability to learn and adapt its behaviors based on experience. This requires some form of memory. An agent may have rules that modify its rules of behavior.

The ABMS approach has the unique capability to represent the decentralized decision-making process that takes place among various building agents on both short- and long-term behaviors regarding energy policy and price. This modeling capability, which is not present in traditional building stock modeling tools, will be particularly important to understand the complex processes underlying the energy use of commercial buildings (as the consumer agents) and their behaviors and energy conservation strategies in energy demanding areas and restructured electricity markets.

The overall process of the entire ABMS process consists of several states. When the simulation starts, it firstly initializes all the agent models according to the specifications of the simulation. After all agents have been reset and initialized, the simulation goes through two loops until the end of simulation. The agent loop searches every agent in the environment and updates their states one by one. This update process happens in every time step of the time loop until the total number of iterations reaches the predefined duration of simulation. This ABMS process can be illustrated as Figure 39.

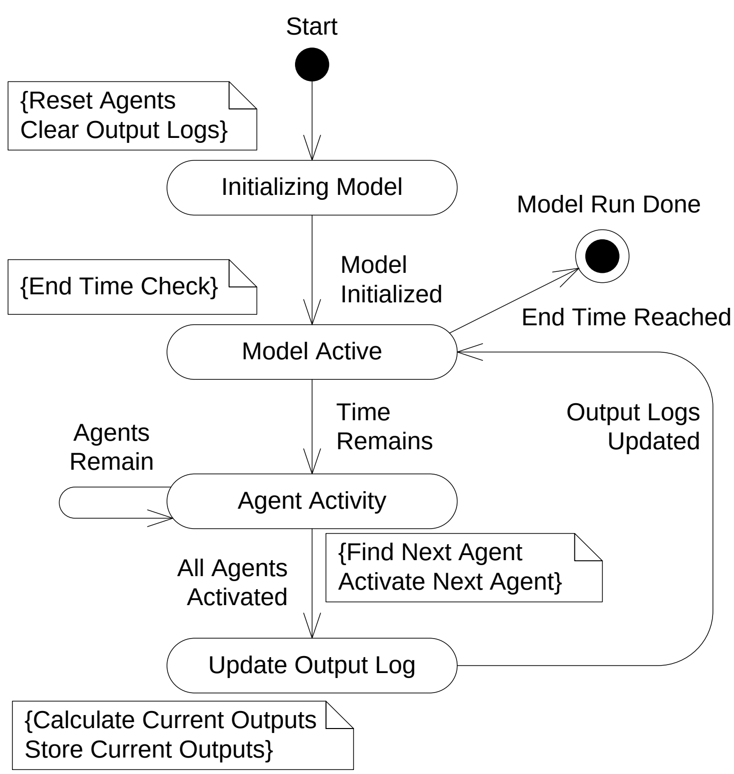


Figure 39 UML state diagram for the proposed ABMS environment [Adapted from North & Macal (2007a)]

5.2 Implementing an ABMS Model

Typically, the procedure for building an ABS system includes four major steps. First, one should identify agents and their behaviors. The second step is to define the rules of interaction among agents and their environment. The third step is to implement the model using a suitable programming toolkit. And the fourth step is to debug the model by observing the agents' behavior and analyzing the simulation outputs (Zhi Zhou, 2010). These four steps are illustrated in Figure 40.

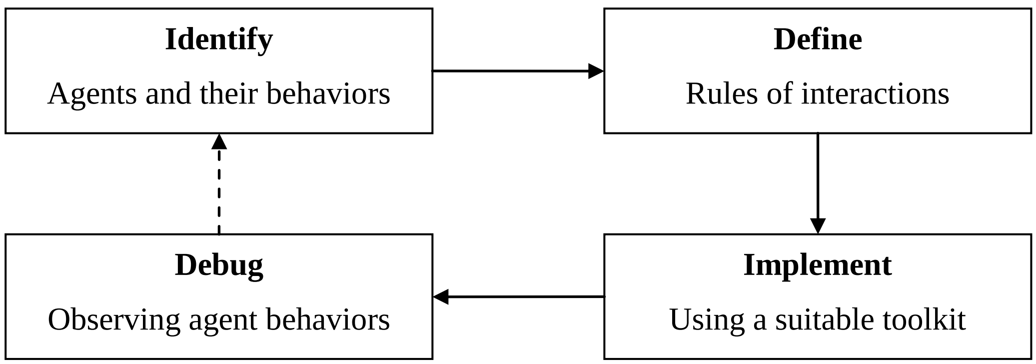


Figure 40 Four major steps for the implementation of an ABMS model

There are a number of existing ABMS application toolkits for developers to use, such as SWARM (Minar, Burkhart, Langton, & Askenazi, 1996), REPAST (M.J. North, Howe, Collier, & Vos, 2007), MASON (Luke, Balan, Sullivan, & Panait, 2003), StarLogo (MIT Media Laboratory, 2000), Netlogo (Wilensky, 1999), etc. Most of them are open source or free licensed. There are also some commercial companies providing ABMS software, such as AnyLogic (XJ Technology, 2012).

In this thesis, the first application (energy policy analysis described in Chapter 6) is implemented in Repast Symphony. The second application (demand response analysis described in Chapter 7) is implemented in AnyLogic 6.

5.3 Adapting ABMS for Building Stock Modeling

The ABMS technique is widely used in many fields, including economics (L. Tesfatsion, 2006), social science (Gotts, Polhill, & Law, 2003; Macy & Willer, 2002; E. R. Smith & Conrey, 2007), anthropology (Axtell et al., 2002; Kohler, 2005), political science (Cederman, 2003), cognitive science (Bandura, 2001), and fundamental sciences such as biology (Emonet, Macal, North, Wichersham, & Cluzel, 2005).

ABMS has been widely used for the auction market (Zhi Zhou, 2010) and power systems analysis (Lagorse, Paire, & Miraoui, 2010). As respect to building-related research, ABMS has been also used as a common technique to model occupant movement under disaster and emergency conditions (Manley & Kim, 2012; Uno & Kashiyama, 2008), patient movement (Kanaga & Valarmathi, 2012), and HVAC system control (van Breemen, 2001). ABMS has been introduced into the building stock modeling by connecting prototypical buildings to the transmission buses of the power system (Fei Zhao, J. Wang, V. Koritarov, & G. Augenbroe, 2010b). It has also been introduced to modeling various retrofit decisions of commercial building owners for policy analysis (Zhao et al., 2011). Findings of the abovementioned literature have proven that ABMS is a feasible and sufficient tool to tackle some intellectual challenges in building stock modeling.

5.4 Concluding Remarks

This chapter is a general introduction of the agent-based modeling and simulation. By reviewing the existing literature of using ABMS, especially for buildings related topics, this chapter recommends that ABMS is a feasible and sufficient tool for building stock models.

6 MODELING LARGE-SCALE RETROFIT FOR POLICY ANALYSIS

6.1 Introduction

The previous chapters have proposed and evaluated a framework to modeling the physical characteristics of building stocks. This chapter, as the first test case, is an application of the proposed framework regarding behavioral and economic characteristics of building stocks in the context of building energy efficiency and retrofit.

Achieving higher energy efficiency at commercial buildings demands action by both policymakers and end users. Governments and societies, through policymakers, have developed regulations and goals for building design and retrofit, especially for commercial buildings. These goals must be achieved through a combination of market transformation activities and technology developments. Although the innovation and adoption of new technologies will be important, the development of strategies for deploying existing and emerging technologies at the required speed and scale is the most challenging factor. To verify whether an energy efficiency plan is achievable in the long term and to evaluate whether an energy reduction goal is met at a given time, researchers must be able to estimate the energy performance of an entire building stock over time. As this assessment is predictive, we cannot rely on metered usage data. In the implementation phase of a retrofit strategy, it is conceivable that metered usage data and/or auditing of individual buildings in the stock could be used to adjust policies, but indeed require intensive data collection and computation expenses. From the perspective of the end user, building owners have diverse attitudes toward policies, incentives, and acceptance levels in terms of adopting energy efficient technologies for their buildings. Hence, to serve the need for policies that address energy efficiency, a building stock energy model must be capable of reflecting current energy performance and projecting the result of future interventions that result from policies and decisions from policymakers and building owners.

To estimate the energy consumption and the CO_2 emissions of building stocks over time, researchers have developed various modeling methods. Groups in Canada (Swan & Ugursal, 2009), the United Kingdom (Kavgic et al., 2010), and the United States (Martinez-Moyano et al., 2010) reviewed some of the existing building stock models. Most existing top-down models are too general to capture the impact of physical interventions to building design and operation, whereas most existing bottom-up models are too computationally intensive to model diverse retrofit technologies and owner preferences (regarding energy and cost). To contribute to the building stock modeling community from a different perspective, Martinez-Moyano, Zhao, et al. (2011) proposed an agent-based approach to tackling this issue and developed a prototype called CoBAM. The objective of the CoBAM project is to study infrastructure, policy, and behavioral factors relevant to meeting sector-wide energy efficiency targets by developing an agent-based model of the commercial sector.

This chapter uses the prototype-based building stock model proposed in Chapter 4, and joins it with the agent-based modeling and simulation (ABMS) technique to capture the interactions of individuals in the building stock.

This chapter is organized as follows. Section 6.2 presents the methodology and the framework of modeling this problem, including all the assumptions and modeling details. Section 6.3 describes the implementation of the methodology into an ABMS platform with different agent states. Section 6.4 demonstrates the capabilities of the proposed modeling method by applying it to a test case. In the end, Section 6.5 concludes.

6.2 Methodology

In the development of the model, we have used knowledge and insights about the commercial buildings sector identified in the literature and as reported in Martinez-Moyano et al. (2010). In addition, we draw on public data sources and on the modeling approach used to characterize sector participants and their decision and interaction processes. In general, there are a number of physical and behavioral characteristics of the commercial building stock that need to be addressed. These characteristics are categorized into five major "portfolios". Figure 41 illustrates such five major portfolios and their relationships in the proposed model.

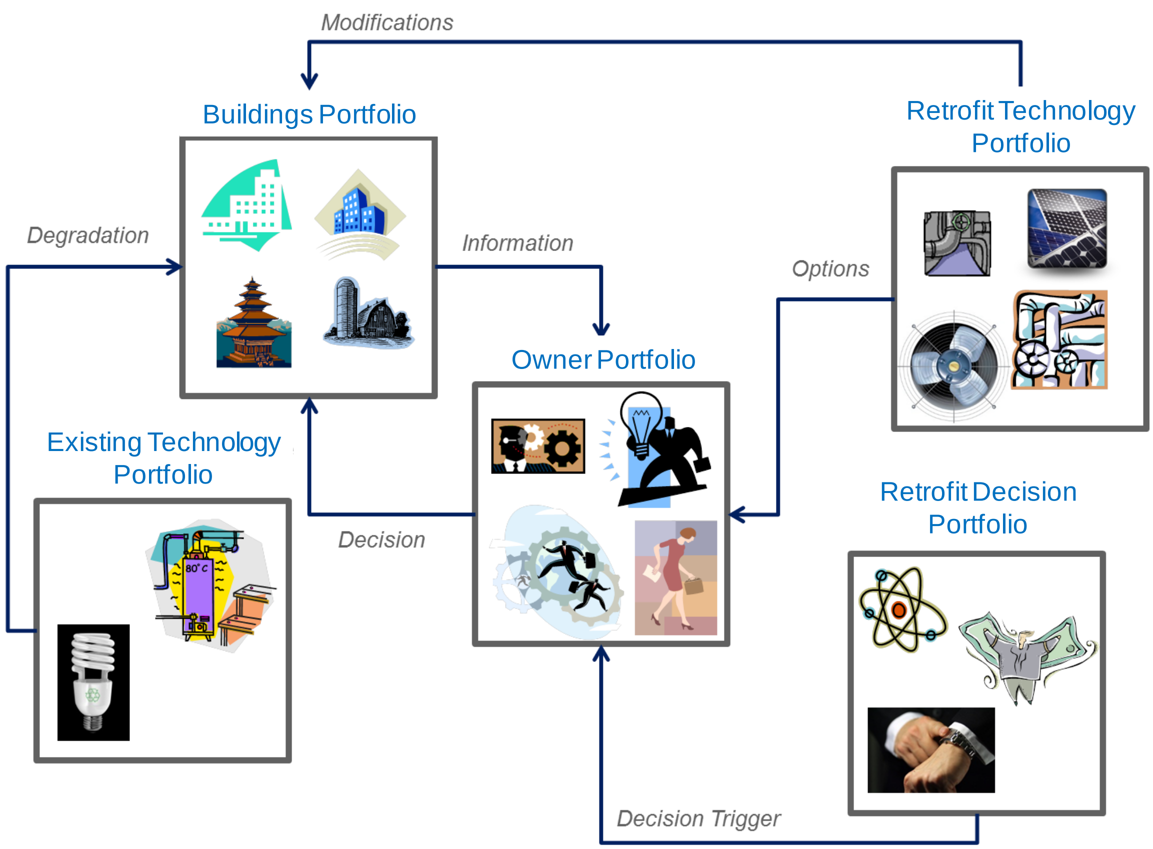


Figure 41 Desired interaction process of the building stock model [Modified from (Martinez-Moyano, Simunich, et al., 2011)]

6.2.1 The Buildings Portfolio

This method uses the normative building energy model as the engine to solve each agent behavior. As introduced in Chapter 2, this quasi-steady state building energy calculation approach is based on ISO 13790 and other supporting standards. These standards provide different types of calculation methods, including a seasonal or monthly method, a simple hourly method, and a detailed simulation method. In this chapter, the monthly method is implemented to serve the objectives.

A set of prototypical building energy models in the United States are adapted in this study. Chapter 4 describes these prototypical buildings and the method of aggregating them to estimate energy interventions in details. In each simulation time step, each prototypical building model is calculated by the normative model to get its energy outputs.

6.2.2 The Existing Technology Portfolio

The energy efficiency of building systems degrades every year. In this study, the building performance degradation process is captured with, and defined as, the annual degradation ratio (ADR). The building energy performance decreases by applying a set of degradation factors to the input parameters. For a degrading building parameter j of building agent i, its value at year (t+1), denoted as $X_{i,j}^{(t+1)}$, is:

$$X_{i,j}^{(t+1)} = (1 + ADR)X_{i,j}^{(t)}$$

According to this degradation function, the performance of each building component is consistently reduced every year until system maintenance is performed to that component. In that case, $X_{i,j}^{(t)}$ is reset to its initial value. New technologies can also be applied to achieve higher performance than used for the initial value.

To quantify building performance degradation, Brown et al. (1996) reviewed past studies of the persistence of energy savings from demand-side management programs and determined an average annual degradation of 0.05~0.20. Hu (2009) surveyed multiple sources in the literature and concluded that the average degradation coefficient due to the partial load operation of heat pumps is 0.10~0.26 for heating and around 0.066 for cooling. In addition, CEN/TC 169 (2006) showed a normative annual maintenance factor of 0.20 for lighting power. In this study, three building model parameters are considered to degrade annually: (1) energy use intensity of the lighting system (ADR_{light}, unit:

W/m^2), (2) the cooling system COP [coefficient of performance] (ADR_{cool}, unit: kW/kW), and (3) overall efficiency of the heating system (ADR_{heat}, unit: kW/kW). In reality, the ADR values vary by case and have relatively significant impacts to the projection of building energy efficiency levels. Thus, multiple scenarios of degradation shall be considered when applying this model to compare policy making decision options. In this prototype, we conservatively assume the values of ADR_{light}, ADR_{cool}, and ADR_{heat} to be 0.05, −0.05, and −0.05, respectively. Using these values means that the power intensity of lighting fixtures increases by 5% every year, and the efficiencies of cooling and heating systems decrease by 5% every year.

6.2.3 The Retrofit Technology Portfolio

As described in Chapter 4, a building stock model has to be capable of effectively predicting the relative energy savings of buildings after energy retrofit. Previous research studies have established a methodology to quantify the result of incorporating energy efficiency measures, or retrofit, into buildings at the scale of a building stock (Clarke et al., 2004; Huang et al., 1991; Jones et al., 2001; Y. Yamaguchi et al., 2004; Zhao et al., 2011).

In addition, demand response behaviors of building stocks also change the value of building parameters over time. A generic formula of the abovementioned interventions, as proposed by Zhao et al. (2011) and Zhao et al. (2010b), is

$$X_{i,j}^{(t+1)} = f_j\left[X_{i,j}^{(t)}\right], \tag{6-1}$$

where f_j is the intervention function that quantifies an update to a specific building parameter j.

In the Appendix of the thesis, we list the specifications of modeled retrofit technologies in the proposed application. Building parameter values are denoted as follows: $X^{(t)}$ is the value at year *t*, $X^{(t+1)}$ is the value at year (t+1), $X^{(0)}$ is the initial value at the beginning of simulation, and $X^{(retro)}$ is the initial value after the previous retrofit. Sources of these cost values include U.S. EIA (2009), Navigant Consulting (2007), Crawley (2008), Augenbroe et al. (2010), Wulfinghoff (2000), ISO (2008), and Mewis (2010). We have not yet found reliable references for the underlined values.

In addition, we organize the retrofit technologies are organized under three levels:

- Category: Building functional systems
- Energy efficiency measure (EEM): Generic ways to improve building energy performance
- Retrofit Technology: Specific technologies available in the market

6.2.4 The Owner Portfolio

The owner portfolio defines *when* for building owners to consider retrofit.

<u>Owner Characteristics</u>

Different from physical buildings, owners are the behavioral perspective of buildings. Each building is owned by only one owner who decides when and how to retrofit the buildings. Different building owners have different attitudes towards energy retrofit. A thorough characterization of owner types can only rely on industry-wide surveys. We have studied literatures including the report *Who Plays and Who Decides* (Reed, Johnson, Riggert, & Oh, 2004) based on CBECS 2003 and then came up with a typology of commercial building owners and their corresponding behaviors. These are indeed assumptions rather than facts, but they are meanwhile abstractions of the real world. Table 19 lists aspects, typology, and retrofit behaviors of each type of owner.

Table 19 A typology of commercial building owners based on their retrofit behaviors

Aspect	**Typology**	**Retrofit Trigger Mechanism**
Energy Efficiency Goal	Leadership	More aggressive energy efficiency goal than average
	Average	Average energy efficiency goal
	Follower	Less aggressive energy efficiency goal than policy required
Ownership	Government owned	Mandatory energy efficiency requirement after a specific year
	Non-government owned	No mandatory energy efficiency requirement
Occupancy	Leased	Retrofit opportunities are especially evaluated when each lease period ends
	Owner occupied	No special evaluation for retrofit opportunities

In this study, each owner is modeled to have only one typology under each aspect. Every time when the retrofit trigger mechanism is met, the owner with that typology is triggered to make a decision by evaluating the alternatives of retrofit technologies, based on the owner's retrofit decision scenario. These scenarios are defined in the retrofit decision portfolio.

Triggers for Retrofit Decision Making

Once a building owner has set up the energy efficiency goal of the building, building starts to have performance degradation during operation. At some point of this process, the building owner has to make a decision: retrofit or not. The mechanism to determine the decision making time, is defined as a retrofit "trigger" in this model. There are mainly three types of triggers, representing three situations when a owner decides whether to retrofit:

- Energy use intensity (for all owner types): When EUI of a building stock reaches its threshold, retrofit evaluation is triggered.
- End of lease (for owners that are labeled as Leased under occupancy): At the end of each lease, even though if the EUI may not reach the threshold, the owner evaluates retrofit
- Incentives (for owners that have decision types as Economic-based or Multi-criterion): During the period of incentives, cost-conscious owners are triggered to evaluate the option of retrofit technologies.

After a retrofit decision is triggered, the owner decides how to retrofit according to its retrofit decision typology.

6.2.5 The Retrofit Decision Portfolio

Different from owner portfolio, the retrofit decision portfolio defines *how* to select retrofit technologies.

A Typology of Retrofit Decision Making Scenarios

In addition to the typology of building owners, seven types of retrofit decision scenarios are developed to formulate the objective of retrofit. The explanations of these scenarios are listed as follows.

Table 20 A typology of retrofit decision making scenarios

No.	Scenario Name	Action when retrofit decision is triggered
1	Do not retrofit	Do nothing
2	Undirected retrofit	Choose a random technology from **Error! Reference source ot found.**
3	Directed retrofit	Choose a preselected set of effective technologies
4	Do all available	Choose one technology from every EEM in **Error! eference source not found.**
5	Economic-based retrofit	Choose the most economic technology that meets certain payback requirement; otherwise, do nothing
6	Energy-based retrofit	Choose the technology that produces the most energy reduction
7	Multi-criterion retrofit	Choose the technology that have the highest weighted-average score from the above two scenarios

More specific definitions of scenario (3) and (5) are as follows.

(3) **Directed Retrofit:** Apply all the following technologies in Table 21

Table 21 Preselected retrofit technologies for the scenario of Directed Retrofit

Energy Efficiency Measure (EEM)	Retrofit Technology
Envelope: Roof Renovation	R20 insulation
Envelope: Wall Insulation	R15 insulation
Envelope: Window Upgrade	Double glazing low-e U2.90 SC0.55
Envelope: Infiltration Reduction	Infiltration reduction
HVAC: Cooling and Heating System Retrofit	Retro-commissioning
HVAC: Energy Recovery	Air-to-air heat wheel
HVAC: Pump System Upgrade	VSD pump system
Lighting: Lighting Fixture Replacement	Light-emitting diode
Lighting: Day-lighting Control	Day-lighting sensor system
Lighting: Occupancy Sensor Installation	Occupancy sensor system
Water Heating: Heater Replacement	Improved condensing gas water heater
Appliances: High-efficiency Appliances	Energy Star equipments

(5) **Economic-based Retrofit**: Choose the most economic retrofit technology. If no one is economic (i.e., simply payback period > Time of Cash Flow (year), or NPV<0, or ROI<Discount rate), do nothing.

Definition of Simply payback period:

If a user selects this as the performance indicator, only *Time of cash flow (year)* is required to input. If retrofit technology i is evaluated in year t,

$$SimplePaybackPeriod_{i,t} = \frac{Inv_i}{AnnualEnergyCostSavings_{i,t}}$$

$$= \frac{Investment_i}{\left(EUI_{elec,t} - EUI'_{elec,t}\right) \cdot FloorArea \cdot 0.01Price_{elec,t} + \left(EUI_{NG,t} - EUI'_{NG,t}\right) \cdot FloorArea \cdot 0.00295Price_{NG,t}}$$

where,

Inv_i (Unit: \$): the investment cost of technology i for the prototypical building. Calculation is based on the cost of that technology per unit area (available in the retrofit technology list) and the reference area in the prototypical building (available in the energy calculator).

$EUI_{elec,t}$ and $EUI_{NG,t}$ (Unit: kWh/m2/year): Energy use intensity of electricity and natural gas for the prototypical building, before retrofit.

$EUI'_{elec,t}$ and $EUI'_{NG,t}$ (Unit: kWh/m2/year): Energy use intensity of electricity and natural gas for the prototypical building, after retrofit.

$FloorArea$ (Unit: m2): Conditioned floor of the prototypical building, available in the energy calculator.

$Price_{elec,t}$ (Unit: cents/kWh): electricity prices in year t. The unit conversion factor 0.01 converts from cents to dollars.

$Price_{NG,t}$ (Unit: \$/1000 ft3): NG prices in year t. The unit conversion factor 0.00295 is determined using heating value: 54 kJ/g, density: 0.8 kg/m3, and 1000ft3=28.3m^3.

Definition of Net present value (NPV):

If a user selects this as the performance indicator, both *Discount rate* and *Time of cash flow (year)* are required to input. If retrofit technology i is evaluated in year t,

$$NPV_{i,t} = -Inv_i + \sum_{k=1}^{Time\ of\ cash\ flow} \frac{AnnualEnergyCostSavings_{i,t}}{(1 + DistountRate)^k}$$

where Inv_i (Unit: \$) is the investment cost of technology i for the prototypical building. Calculation is based on the cost of that technology per unit area (available in the retrofit technology list) and the reference area in the prototypical building.

$$\begin{aligned} &AnnualEnergyCostSavings_{i,t} \\ &\qquad = \left(EUI_{elec,t} - EUI'_{elec,t}\right) \cdot FloorArea \cdot 0.01Price_{elec,t} \\ &\qquad + \left(EUI_{NG,t} - EUI'_{NG,t}\right) \cdot FloorArea \cdot 0.00295Price_{NG,t} \end{aligned}$$

Here we use constant energy prices at year t when decision is made. Definitions of the rest terms are defined previously.

Definition of Return on Investment (ROI)

If a user selects this as the performance indicator, both *Discount rate* and *Time of cash flow (year)* are required to input. If retrofit technology i is evaluated in year t,

$$ROI_{i,t} = \frac{AnnualEnergyCostSavings_{i,t} * TimeOfCashFlow - Inv_i}{Inv_i}$$

where all terms are defined previously.

Energy Prices Forecasting Models

Energy prices are important to the evaluation of economics of retrofit technologies. The U.S. EIA (EIA, 2011) and the electricity market module of the NEMS (EIA, 2009) have been conducting serious research to forecast energy prices of electricity and natural gas in each state of the U.S. However, the fairly stable forecast results of energy prices is also considered to be not enough to stimulate energy retrofit (Hanson & Laitner, 2004). In this study, we have developed two simple methods to forecast energy prices, in addition to the EIA's forecast results. As shown in Figure 42, the single exponential forecast method yields to a significantly increasing energy price trajectory, whereas the double exponential method returns a fairly stable prediction, which is similar to the EIA's prediction. In this application, both price predictions as well as the EIA's prediction can be used in the analysis.

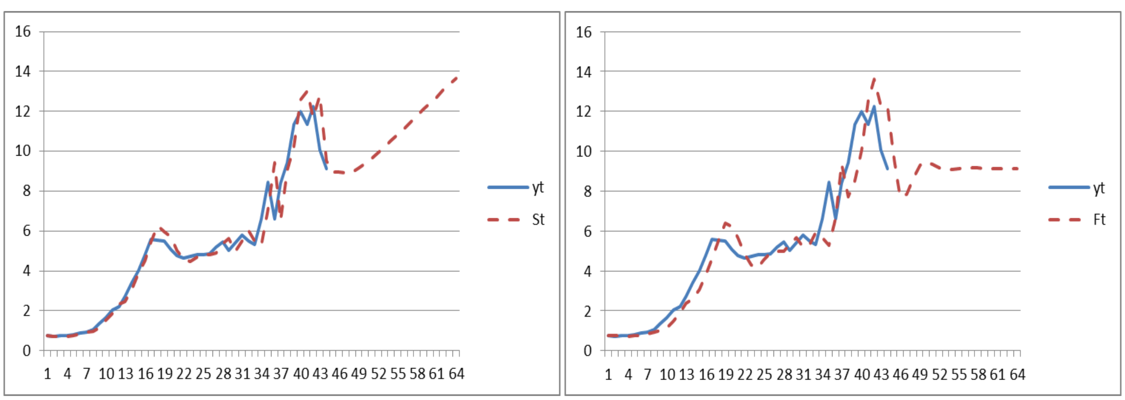


Figure 42 Energy forecast methods: Single exponential (left) and double exponential (right)

6.3 Simulation Framework: Agent Based Modeling and Simulation

In the development of this application, we use an agent-based modeling approach. Agent-based modeling and simulation is a technique for bottom-up modeling that provides an alternative perspective to those that can be attained by using optimization or general-equilibrium approaches (Michael J. North & Macal, 2007b). In agent-based simulations, system behavior emerges from the behaviors of interacting agents. An agent can be an autonomous and potentially self-directed entity that is characterized by a set of attributes. Normally, in agent-based models, agents are situated in a system in which they interact with each other and their environment. The behavior of an agent is usually driven by its goals. In achieving these goals, specific and predefined rules guide the agents' actions when interacting with the other agents. An agent has the potential to learn based on environmental information and a set of predefined rules. Climate and policy impacts are modeled as the environment.

Technically, this test case is implemented in the open-source Repast Symphony environment[5]. The architecture of the model is designed in generic terms to allow for scalability of features, number of agents modeled, and features of the agents. This development philosophy allows for flexibility in model components and offers scalability potential to avoid the need to restructure the model in major ways when additional detail or complexity is added.

In the ABMS, every building owner agent determines its own behavior when it gets activated. These behaviors can be modeled as a combination of performance degradation and energy retrofit.

As an overall impact of performance degradation and energy retrofit, building model parameters over time are modeled as time series, each year's state of which depends on its state in the previous year:

[5] See http://repast.sourceforge.net/.

$$
\boldsymbol{X}_{i,j}^{(t+1)} = \begin{cases} \boldsymbol{X}_{i,j}^{(t)}, & if\ PI_i^{(t)} \leq PI_{th}^{(t)}, nondegrading\ param. \\ (1+ADR)\boldsymbol{X}_{i,j}^{(t)}, & if\ PI_i^{(t)} \leq PI_{th}^{(t)}, degrading\ param. \\ f_j\left[\boldsymbol{X}_{i,j}^{(t)}\right], & if\ PI_i^{(t)} > PI_{th}^{(t)} \end{cases}
$$

where $\boldsymbol{X}_{i,j}^{(t+1)}$ is a set of building model parameters of agent i at year (t+1), and $\boldsymbol{X}_{i,j}^{(t)}$ is its value at year t when the building owner decides whether to retrofit. This process is computed within ABMS. Figure 43 illustrates the UML State Diagram of this process.

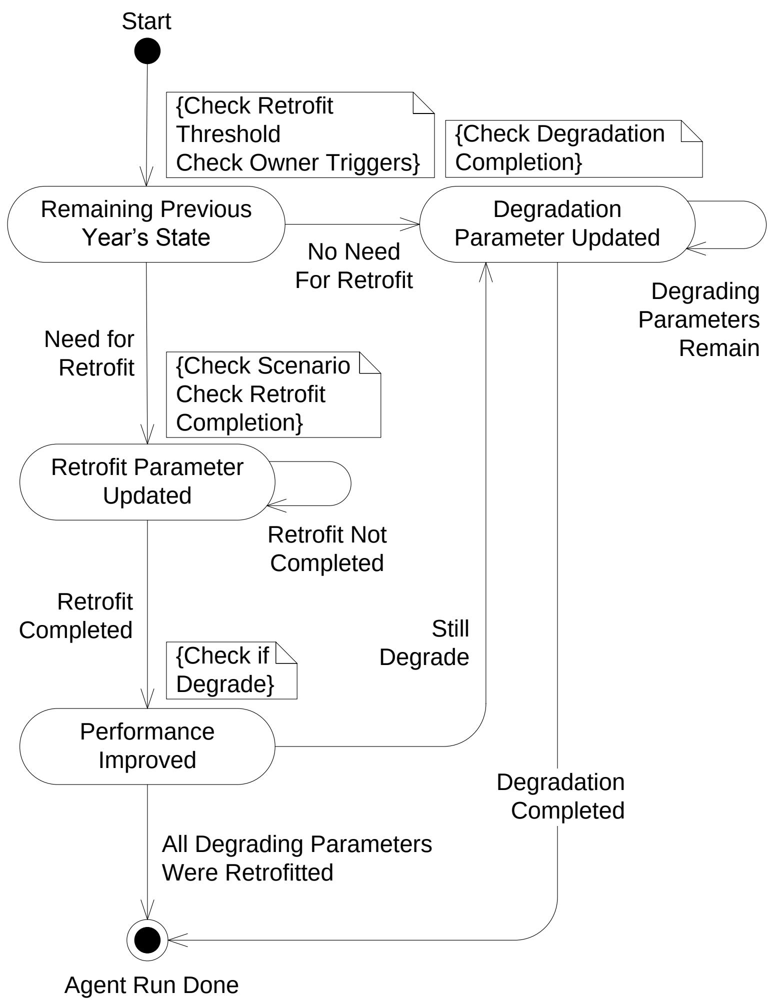


Figure 43 UML state diagram for commercial building agents

Figure 43 depicts the following steps within each time step of the simulation:

1) The agent initially remains at its state in the previous time step.

2) If the performance indicator of the agent does not reach the retrofit threshold, the degradation loop starts to look up and update all degradation input parameters for the energy calculator. This action then ends the agent's behavior at this time step.
3) If the performance indicator of the agent reaches the retrofit threshold, the retrofit loop starts to look up and update all retrofit input parameters for the energy calculator.
4) When the retrofit loop is finished, the degradation is then started as step 2.
5) Agent finishes the update process and brings its state to the next time step.

6.4 A Case Study

To demonstrate the use of the proposed ABMS building stock model, we have created a population of 288 building stocks based on all 16 building types, two U.S. climate zones (4A and 5A), and three vintage categories (new, post-1980, and pre-1980) all located in six representative cities of the region being modeled (i.e., all located in Illinois, specifically Chicago, Belleville, Bloomington, Quincy, Rockford, and Springfield, as shown in Figure 44).

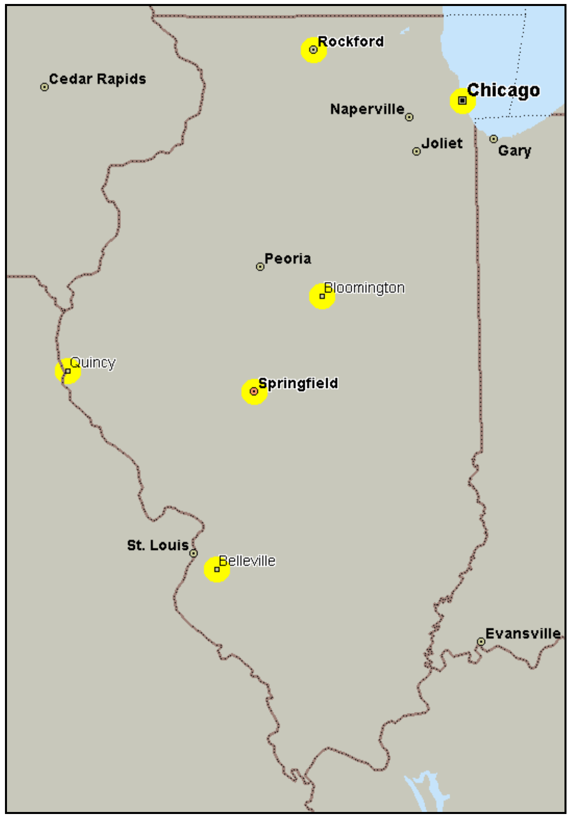


Figure 44 A map of the six selected cities in the state of Illinois, United States

6.4.1 Baseline Generation

As proved in Chapter 4, the prototype-based building stock model is only capable of prediction the relative impacts of interventions compared to the building stock baseline, it is important here to create a baseline model before applying any interventions. Here we first assume that the floor area fractions of the created building stocks follow their original fractions in the DOE reference buildings, which were derived based on the McGraw Hill new construction database (McGraw Hill, 2011). As the next step, we proportionally increase all the floor areas, until the regional total CO_2 emission meets the estimated total CO_2 emission by the Vulcan database (Gurney et al., 2008).

6.4.2 Scenarios of Simulation

In this case, to limit the degree of freedom of the problem, owners are all defined with average energy efficiency goals and they possess non-governmental, self-occupied buildings. Six retrofit decision scenarios are modeled: (1) Do not retrofit, (2) Undirected retrofit, (3) Directed retrofit, (4) Do all available, (5) Economic-based retrofit, and (6) Energy-based retrofit. The definitions are in the previous section.

These three scenarios are designed to (1) capture likely extremes in a continuum of possible decision options that building owners may face, and (2) identify the resulting overall behavior if these decision strategies are adopted by building owners. We place these three scenarios into a “step-down” energy policy, which s: “Buildings are required to maintain their 2005-level energy use before 2010, reduce 10% by 2010, and reduce another 10% by 2020.”

This energy efficiency policy has a similar goal with the Better Buildings Initiative (BBI) in the United States (20% improvement in building energy efficiency by 2020).

6.4.3 Analysis Results

<u>The Effect of Randomness</u>

First of all, we performed a sensitivity analysis to the random number generation in the model. This gives us a better sense of how much randomness exists in the model. This has been done in the undirected retrofit scenario under Policy 1, in which building stocks randomly choose retrofit technologies. As shown in Figure 45, the overall trends of the regional averaged delivered EUI remain almost identical in ten identical runs with different random seeds. This finding proves that although there are stochastic components in this model, we do not need to perform the simulation multiple times to get an average result. The randomness is negligible.

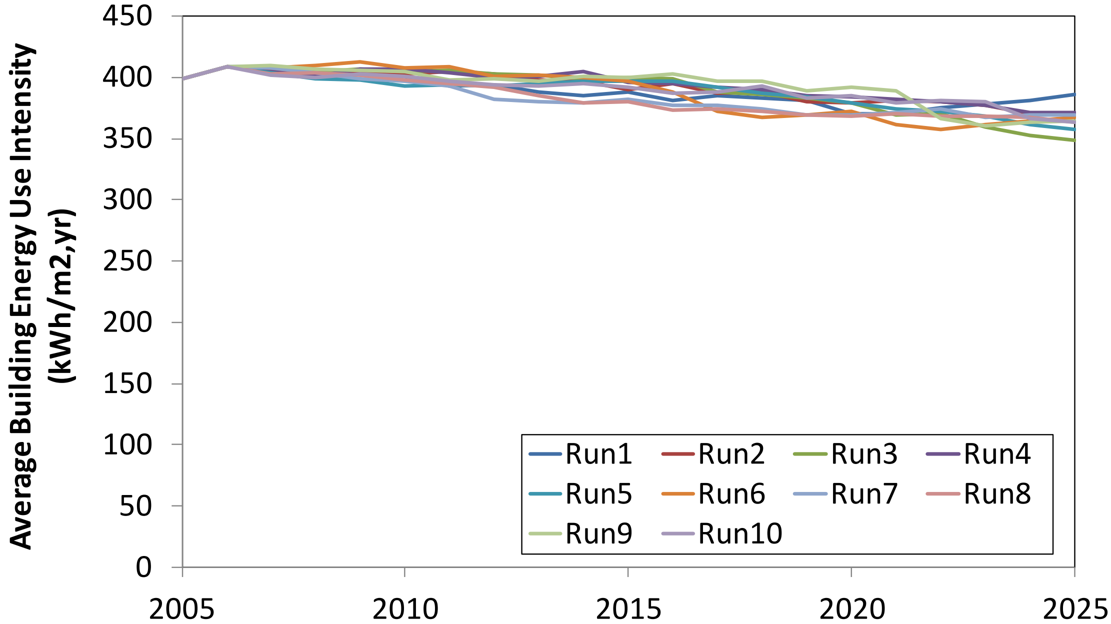


Figure 45 Undirected retrofit with different random runs

<u>All Scenarios under One Policy</u>

We then apply all six scenarios in one policy environment, the Policy 1, to compare different energy efficiency decision scenarios in terms of their effectiveness of energy efficiency improvement.

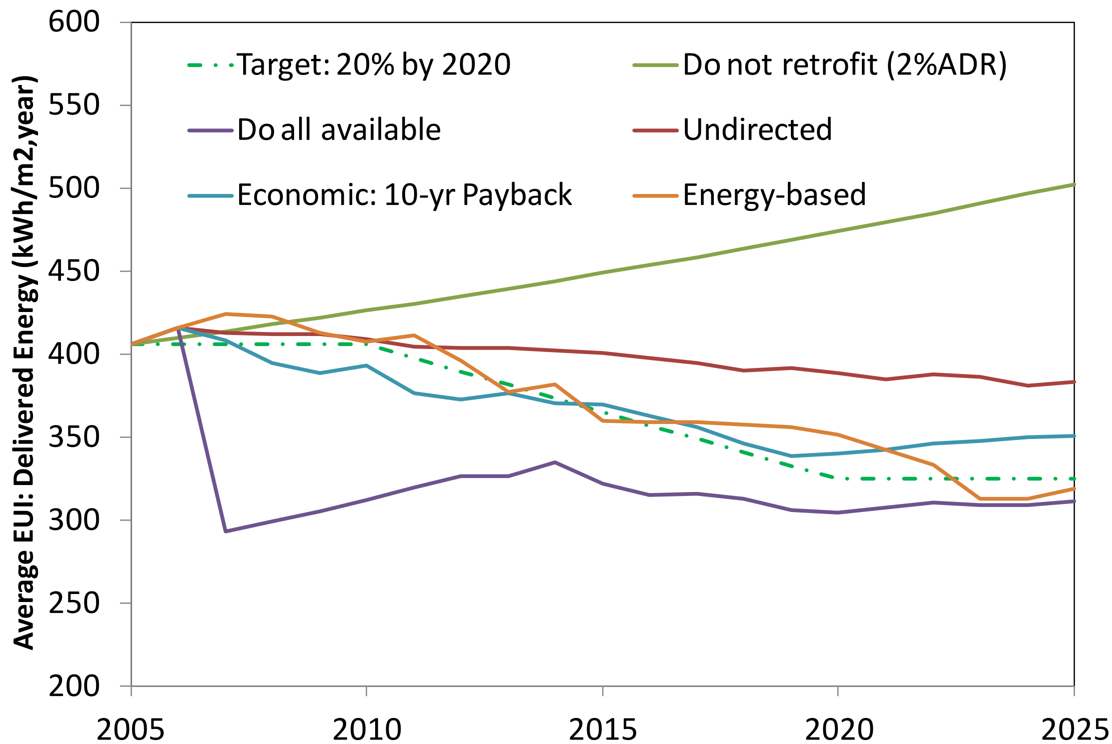


Figure 46 Growth of energy use under different retrofit decision types

As shown in Figure 46, the *Do not retrofit* scenario under generates continually increasing EUI because no retrofit has ever been adopted, making the building stock increasingly inefficient. This trajectory can be considered as the "business-as-usual" path with no improvements attempted. The other five scenarios, under the pressure of energy efficiency policy, all tend to reduce their EUIs gradually. By comparing the trajectories of the scenario, we can see the order of effectiveness of the four scenarios, from low to high, is: Undirected < Economic-based < Energy-based < Do all available. This finding implies that better guidance, better evaluation of retrofit technologies, and more retrofit would yield to higher energy efficiency and retrofit effectiveness.

We further compare the energy efficiency with the Policy 1 target: 20% improvement by 2020. We notice that only the Energy-based and Do all available scenarios have just met the target, which represent the situation that the owner should either perform energy analysis to select retrofit technologies, or apply a big package of ones. The other four scenarios are not capable of meeting the target, including the Economic-based scenario. This indicates that without additional incentives provided by the policy makers, building owners do not have the financial benefit to meeting the 20% energy efficiency saving target.

By further looking at the CO_2 emissions of this case (shown in Figure 47), we can draw same conclusions as mentioned above.

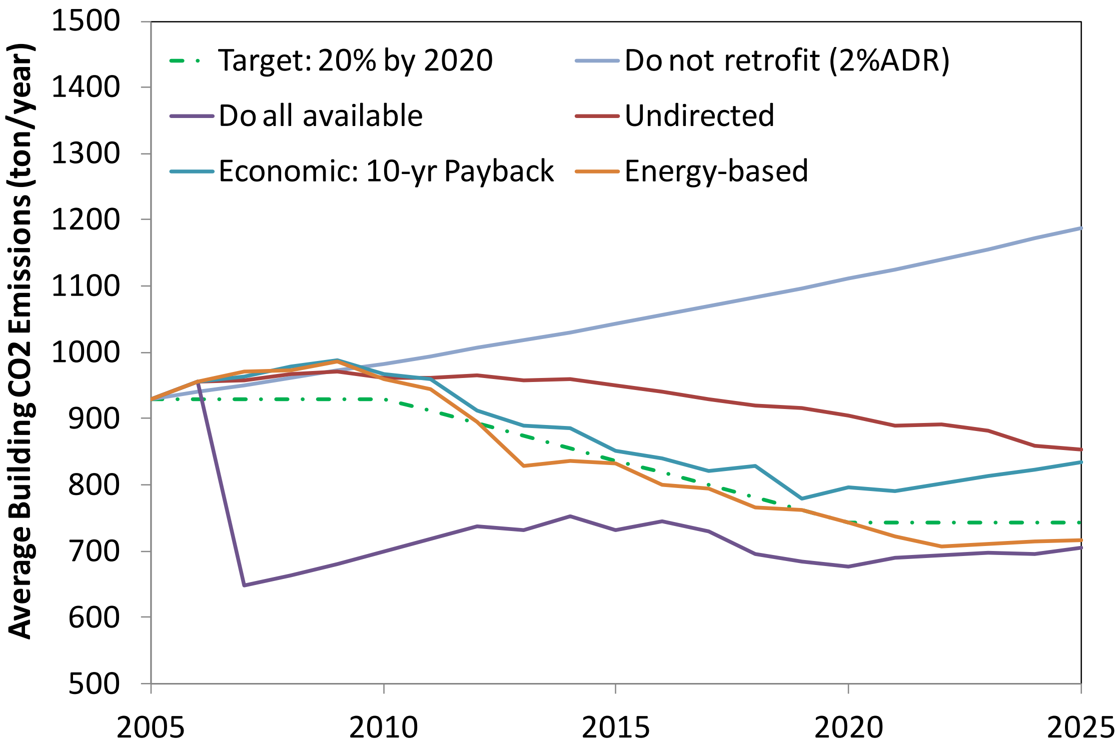


Figure 47 Growth of CO_2 emissions under different scenarios

<u>Different Payback Expectations and Incentives</u>

The Economic-based scenario simulated previously is based on a 10-yr simple payback period to evaluate the best retrofit technology. If owners are willing to consider shorter or longer payback periods, the regional energy efficiency might be different in future. To learn more about this factor, we apply the Economic-based scenario under three different payback periods: 5, 10, and 15 years.

In addition, we apply a package of incentives to the following technologies, so they are more appealing to Economic-based building owners. Incentives are modeled as reduction of the technology investment price by 30%. The technologies with incentives are:

- Energy Star equipment
- Automatic H/C plant control and scheduling
- Fault detection and diagnostics (FDD)
- R5 insulation for walls
- VSD pump system
- LED lighting
- Occupancy sensor system

Figure 48 depicts the comparison of the abovementioned scenarios. As a result, even with 30% incentives applied to several technologies, none of the scenarios will yield to a 20-year end EUI less than 20% of the baseline. Within the predicted trajectories, the three most efficient retrofit scenarios are the ones with longer payback periods. This proves the fact that people willing to pay more and expect longer payback are taking the more expensive but also efficient technologies. Additionally, by comparing the same scenario with and without incentives, we realize that incentives in general improves the energy efficiency, but they are more effective to those owners willing to accept a longer payback period, in this case, 10 years.

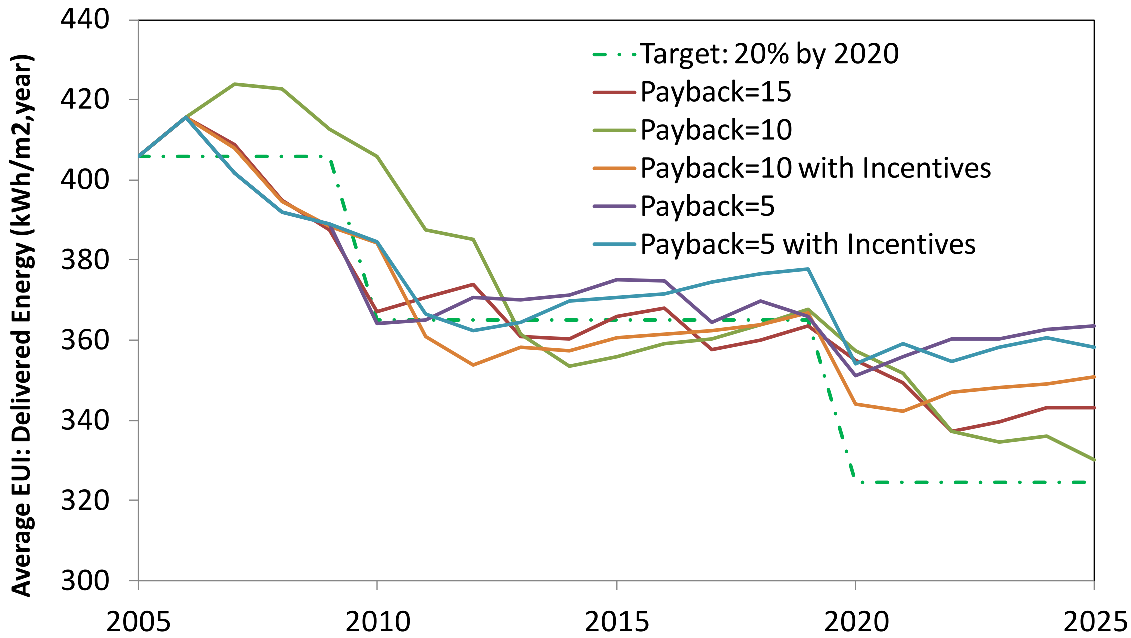


Figure 48 EUI prediction under different max simple payback periods

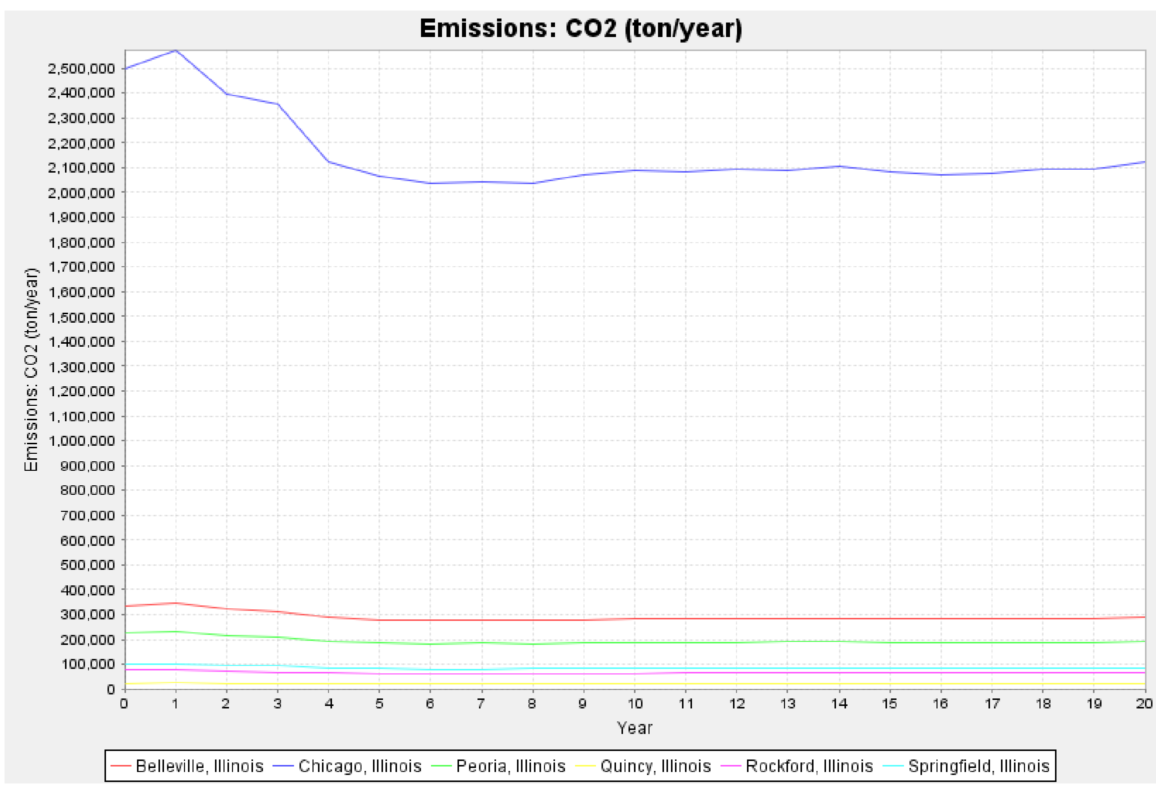


Figure 49 Long-term CO2 emission prediction of the six cities

We further look into the Economic-based scenario by checking the predicted CO2 emission reductions of the six cities. The prediction is shown in Figure 49, which indicates that Chicago contributes the most to regional CO2 emission. This simulation is based on a 10-year payback period, which stabilizes the regional CO2 emission by about 15% less than its value in the baseline.

We then retrieve the frequencies of retrofit technologies adopted during the 20 years of performance degradation and retrofit. As shown in Figure 50, retro-commissioning is the mostly chosen technology given its low cost and high effectiveness. The technologies below are listed in Figure 50 with their frequencies. These technologies are found to be the most cost effective ones, and deserve R&D investment and incentives from the industry and the government.

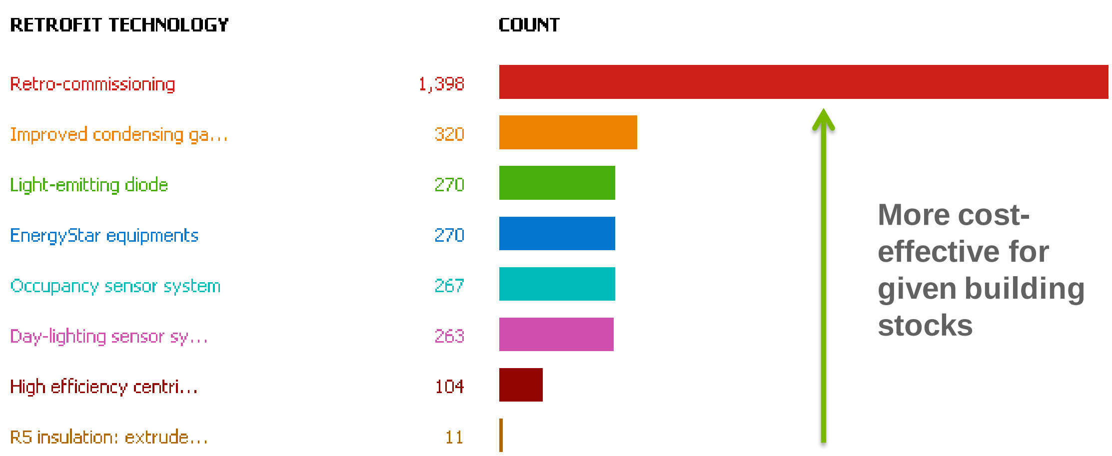


Figure 50 Frequency of retrofit technology adoption

In fact, across the entire region, buildings may have different payback periods for the same retrofit technology. To investigate such difference, the model can further plot the variation of simple payback periods of the abovementioned 8 technologies in the box plot below. In Figure 51, retrofit technologies such as day-lighting sensor, Energy Star equipment, and R5 wall insulation have relatively narrow bands. The other technologies vary from 1 to 10 years in simple payback periods. The condensing gas water heater is found to have the biggest spread across the building stock, meaning that for some buildings it is very cost effective, while for others not.

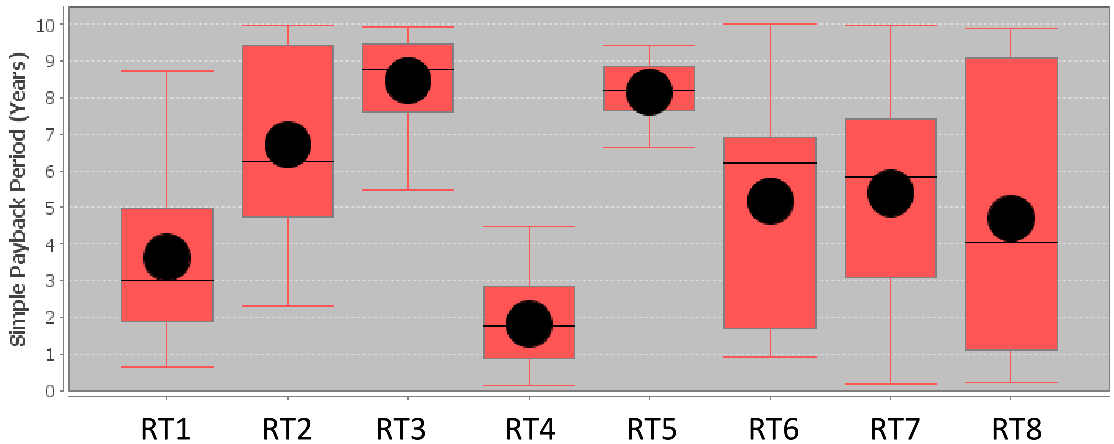


Figure 51 Simple payback periods of the most effective retrofit technologies found in the test

To look more closely into the simulation results and verify the rationale of owner behaviors, we choose one building stock from the modeled state and check its annual expenditure. The selected is a large office located in Chicago. As shown in Figure 52, the building has its majority of delivered energy consumption for internal lighting and appliances. If the building owner is rational, retrofit technologies on these two components should be the most effective.

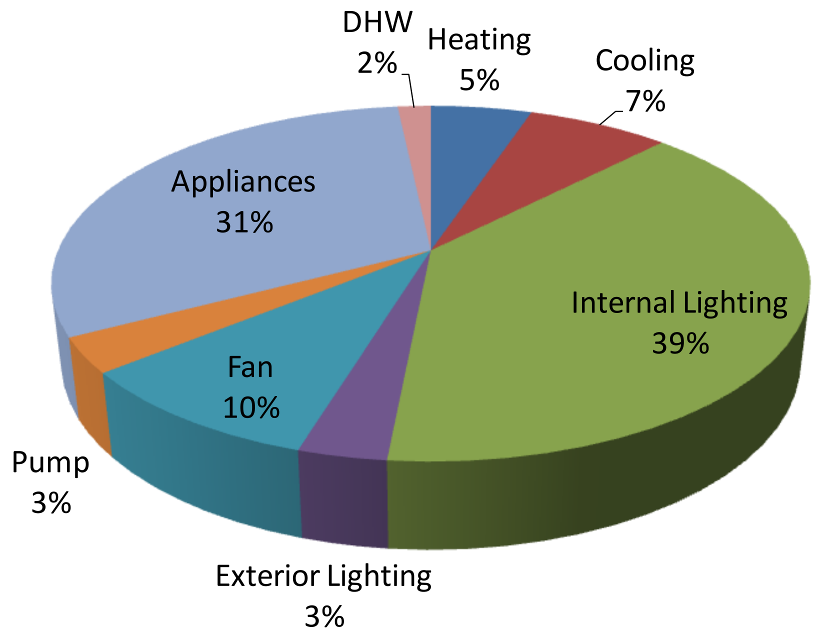


Figure 52 Baseline delivered energy breakdown for the selected building

We then look into the annual expenditure of this building stock, shown in Figure 53. The result shows that after each major retrofit (cost of which are illustrated by the blue bars), the building utility bills (illustrated by the red curve) are reduced in the next year. We also check the yearly behaviors of this building stock and plot it in Figure 54. We notice that LED lighting, Energy Star appliances, retro-commissioning, and the day-lighting sensor system are the technologies chosen by this building stock owner. They are apparently the most cost effective choices for such a building. This finding verifies the decision making mechanism of the proposed model.

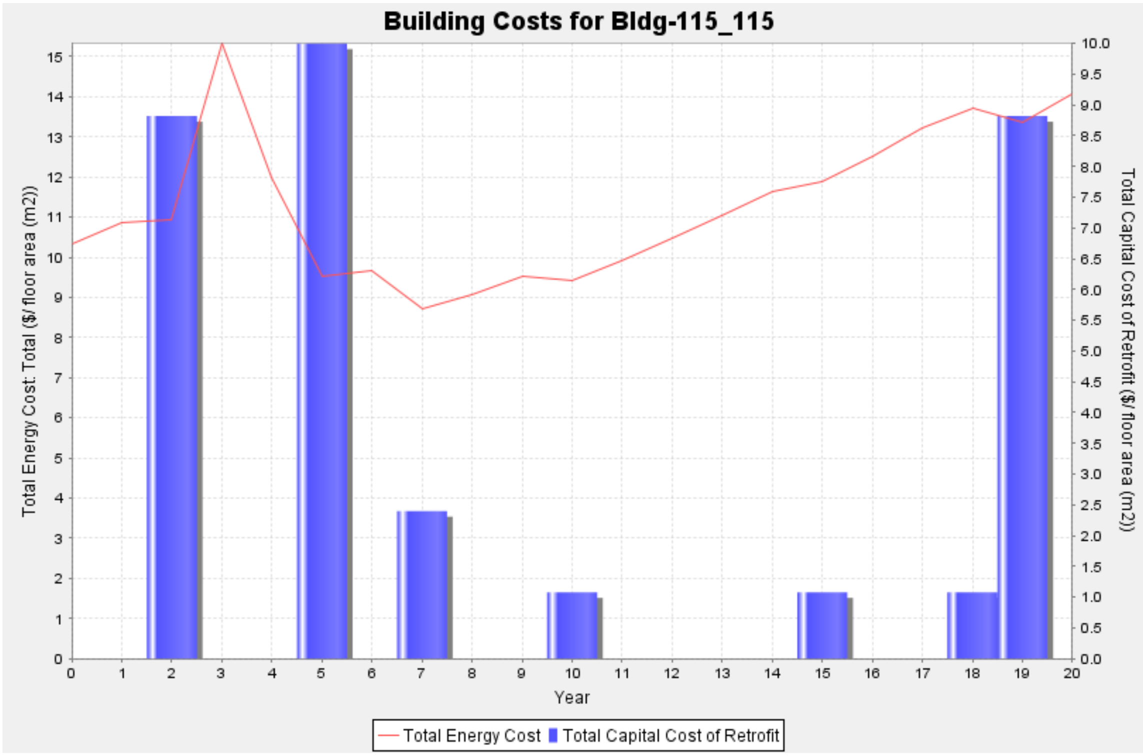


Figure 53 Annual expenditure of one sample building stock

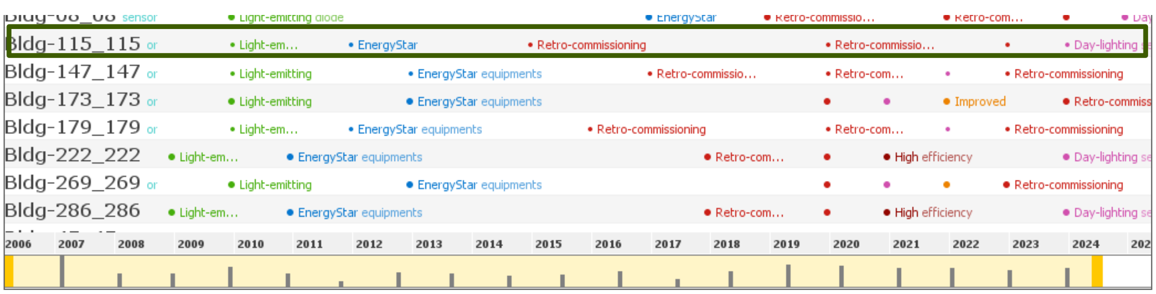


Figure 54 Annual retrofit behaviors of the selected building stock

Energy-based Retrofit: Rank of Technologies by Their Effectiveness

The last thing we investigate from the simulation result is the Energy-based scenario. This scenario is based on the assumption that owners have sufficient knowledge about the impact of retrofit technologies in their own situation (building), and choose the most effective one. Figure 55 depicts the frequency of technology adoption by owners in this region. The top listed technologies, for example, the GSHP, are expected to be the most effective ones and deserve more incentives from the policy maker. This list is location and building composition dependent. Policy makers can use the proposed framework and a tool to generate a list for each city to support energy efficiency policy making.

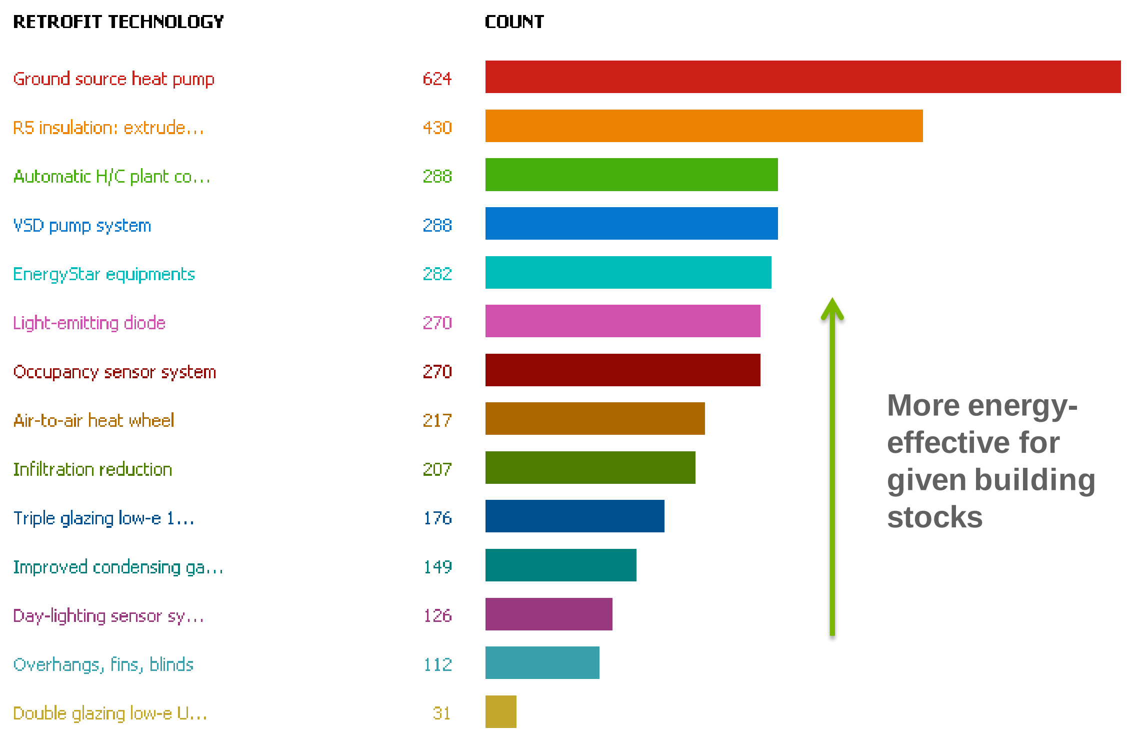


Figure 55 Frequency of technology adoption under the Energy-based scenario

6.5 Concluding Remarks

This chapter proposes an ABMS simulation method to estimate the energy performance of multiple building stocks over time. This model is built up via aggregation of a set of prototypical building designs calculated by a simplified building energy calculator. Both performance degradation and energy retrofit models determine the annual energy performance of each building stock agent. Simulation results suggest that policy-initiated changes to baseline decision thresholds yield adequate results and tend to stabilize the results observed. In addition, simulation results support the idea that promoting energy efficiency technologies, even in a random way, has the potential to yield interesting results in the marketplace.

More specifically regarding the policy under evaluation, 20% energy efficiency improvement by 2020 is almost not achievable for typical building owners, even with 30% of incentives to a set of retrofit technologies. Higher incentives, better design/retrofit guidelines, and a well-served building analysis industry can help leverage the gas between reality and the policy target.

The work described in this chapter implies that achieving commercial building energy efficiency targets most likely depends on the dynamics between the various market participants and the way those dynamics are impacted by different physical and institutional constraints. Studying infrastructure, policy, and behavioral factors relevant to meeting sector-wide energy efficiency targets by developing an agent-based model of the commercial buildings sector generates promising results. In this sense, we are interested in gaining confidence in both the structure of the model and in its simulation output. In addition, to increase confidence in model results, we are looking at data sources that can help us identify trends in behavior of the system and will closely inspect model results and its corresponding explanations with subject matter experts and market participants.

It is also worth noting that from the modeling and simulation perspective, the test cases of this chapter have proven the hypothesis that the method of using a prototype-based building stock model with ABMS provides unique capabilities and comprehensive functions to analyzing the diverse physical and behavioral aspects involved in the large-scale retrofit process.

7 LARGE-SCALE DEMAND RESPONSE ANALYSIS

7.1 Introduction

To demonstrate the potential use of the proposed building stock model, this chapter, as the second major application, applies it to the context of demand response analysis in the transmission network of the power grid.

Electricity markets in a number of countries and several regions of the United States, including in Australia(F. A. Wolak, 2000), England (F.A. Wolak & Patrick, 1997), Spain (Fabra & Toro, 2005), New England (Bushnell & Saravia, 2002), New York (Saravia, 2003), and the Pennsylvania-New Jersey-Maryland Interconnection (Mansur, 2003), have been restructured away from operating as centralized markets to operating as competitive markets. This evolution has dramatically changed how power systems operate. In traditional power systems, supply from committed generation units is scheduled to follow any change in load demand. In a peak load period, the load can be very high, and more generators have to be committed. This usage pattern means that operators must increase their investment in greater generation capacity, which may only be committed for a few hours in a year. Demand response (DR) is an alternative solution to reduce peak loads and adjust the demand in peak times to postpone the investment in new generation capacity. Moreover, in regions with high penetration of renewable energy sources, DR can trigger the change of demand to follow the change of supply.

In general, DR programs enable customers to manage their consumption of electricity in response to supply conditions. For example, many programs have electricity customers reduce their consumption at critical peak load hours or in response to market prices. To achieve this goal, both incentive-based and price-based (U.S. Department of Energy, 2006) DR programs are developed. Incentive-based DR programs offer customers some monetary bonus to reduce load upon operators' request, whereas price-based programs allow customers to voluntarily adjust their demand based on electricity prices, which can be determined through real-time pricing, critical-peak pricing, and time-of-use rates. We develop this study in the context of price-based DR programs.

As one of major utility consumers, commercial buildings consume more than one third of the total end-use electricity in the United States (U.S. EIA, 2009b). To simulate the interplay between the consumers and suppliers in the electricity market, buildings are typically modeled as predefined, aggregated, and fixed-load profiles or demand curves on the basis of historic regional electricity consumption data in the existing literature (Dam et al., 2008; Exarchakos et al., 2009; Vytelingum et al., 2010). To study interventions of load characteristics, Callaway (Callaway, Nov 3, 2009) uses a simple dynamic load model which has aggregated coefficients of the building thermal capacity, resistance, and heat gains. In reality, however, buildings of different types are typically identical (i.e., having identical energy consumption patterns that are determined by weather conditions, design styles, and operational behaviors) and autonomous (i.e., being responsive to electricity prices in different ways). Some other models define loads based on building physics. One example is the Equivalent Thermal Parameters (ETP) method. It is originally applied to transient building energy simulation (Sonderegger, 1978), then simplified and implemented in the GridLab-D software developed by PNNL to simulate every individual building in the power distribution network (Chassin, Schneider, & Gerkensmeyer, 2008; Taylor, Gowri, & Katipamula, 2008).

As a new approach to model systems comprised of autonomous and interacting agents, ABMS provides an ideal way of researching "systems that are built from the bottom." To capture the diversity and dynamics of electricity consumption in buildings based on their design and operations, multiple building stock energy models have been developed to support policy making (Martinez-Moyano et al., 2010). Zhao et al. (Fei Zhao, Jianhui Wang, Vladimir Koritarov, & Godfried Augenbroe, 2010a) developed an ABMS framework based on first-order heat balance equations to estimate the hourly load of commercial building stocks at the regional scale. In this approach, the electricity demand of a building stock is determined by running an hourly quasi-steady-state energy calculation for representative designs in the building stock and scaling the energy use intensity of representative buildings up to the entire building stock by gross floor area. Different building operation schedules are also considered for different building type. This framework estimates large-scale energy consumptions of buildings without expert-driven, massive, transient energy simulations for each building in the stock. Sometimes, massive simulations are not even applicable when the information about buildings in the stock is not adequate. The simplicity of this approach also enables modeling various DR actions of commercial buildings.

To promisingly model the electricity market with DR from commercial buildings, we also use this ABMS platform to analyze the interaction among the consumption behaviors of commercial buildings and the power grid and the corresponding economic consequences under different electricity market competition levels. Autonomous agents have been widely used to model different participants in power systems and electricity markets (Guerci & Rastegar, 2009; Rahimiyan & Mashhadi, 2010; Z Zhou, Chan, Chow, & Kotsan, 2009). There are also some ongoing work on research (McArthur, 2011; Sensfuß, Ragwitz, Genoese, & Möst, 2007; Leigh Tesfatsion, 2011; Weidlich & Veit, 2008; Z. Zhou, Chan, & Chow, 2007) and development (Chassin et al., 2008; Conzelmann, Boyd, Koritarov, & Veselka, 2005; Li & Tesfatsion, 2009; Schoenwald, Barton, & Ehlen, 2004). In this chapter, we model the electricity market as a repetitive, multi-unit auction in which generation companies can bid strategically. In addition, both perfect and duopoly market competitions are modeled to reflect different market structures and investigate how the building energy use varies in different markets.

This chapter addresses two research questions: 1) From the electricity market perspective, how different scales of DR participation will affect the market prices; and 2) From the consumer perspective, how different market competition levels will affect the energy and monetary outcomes of commercial buildings applying DR. In greater detail, this research contributes in the following ways:

1) This chapter integrates a quasi-steady-state, end-use energy model of commercial buildings with electricity market simulation. Given the bottom-up physical model for different building types, this simulation framework is capable of modeling the load reduction of buildings under different scenarios by manipulating building operational parameters.
2) This chapter investigates the influence of different levels of participation in DR from commercial buildings on electricity prices, consumption, and utility costs

using the ABMS approach. Simulation results indicate that the impact is noticeable, and this impact varies with different scales of DR participation.

3) This chapter studies electricity consumption of commercial buildings in markets with different levels of supply-side competition, which illustrate differences in market dynamics and individual behaviors from both supply and demand sides.

7.2 Commercial Building Stocks

In this study, a group of buildings of the same type within the same region is considered a single agent. The hourly electricity demand of each agent is determined by multiplying the total floor area of this building type in this region with the electricity use intensity (in MW/m^2) of its representative design, calculated by the simple hourly method. Multiple commercial building agents can be located in the same region/city, and different regions use different hourly weather files.

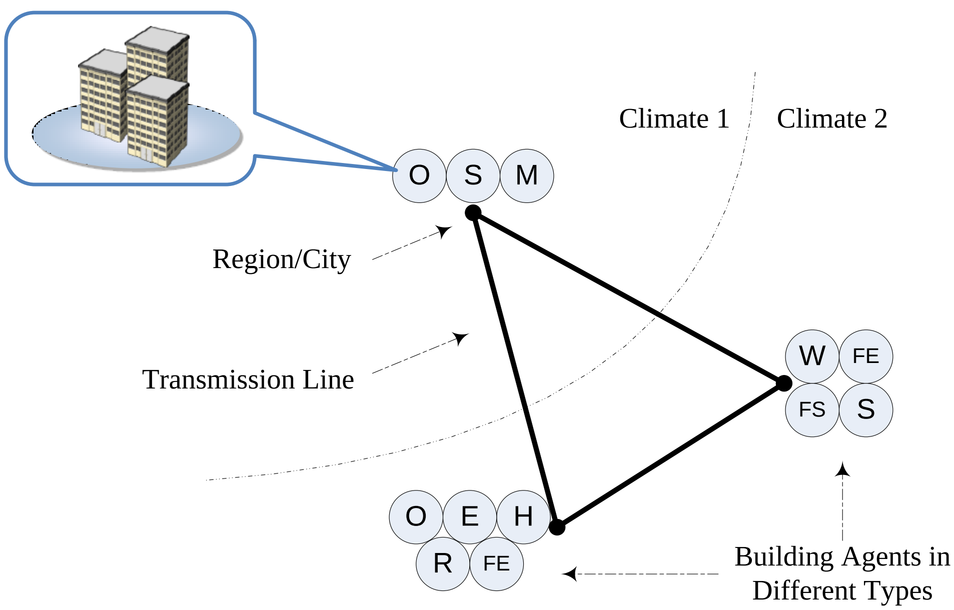


Figure 56 Conceptual relationship among building agents, regions, and transmission lines (Zhao et al., 2010b)

Each building agent requires the specification of a list of input parameters. These parameters are classified into the following categories: program, materiality, HVAC, and equipment.

It is important to determine the input parameters of the representative buildings so that expected levels of accuracy can be achieved. The accuracy of the calculation can be improved by dividing the area of interest into multiple smaller regions and specifying local average data for each building agent if detailed data on building design are available. However, when local building data are not available, which is most often the case, regional statistical data are used instead. The ranges of energy modeling input parameters for commercial buildings by building type in different climate zones were studied, and the corresponding simulation results are checked against the 2003 CBECS data in (EIA, 2006). We adapted these results and developed a prototype for the test cases in the following sections.

Complete sets of input parameters for each representative building with respect to climate zone and building age is stored in a database. When the total floor area, building age (pre- or post-1980), and primary heating source (electricity or non-electricity) are specified for each building agent, the software selects the corresponding input files from the representative building parameter database and the right climate data from the climate database. Input data files then go to the simple hourly model. The calculated hourly electricity demands of building agents are then aggregated to derive the total hourly demand profile of the region.

7.3 Electricity Market Overview

A market is one of many varieties of systems, institutions, procedures, social relations and infrastructures whereby parties engage in exchange. One of the goals of a market is to reduce the cost for carrying out exchange transactions (Roase, 1990).

On the electricity market, during the last twenty years, a process has been undergone worldwide to privatize the state owned electrical power facilities and liberalize the markets for the services based on these facilities. This process moves the electricity industry from vertically integrated monopolies to efficient, separated companies, and replaces the administrated, cost-based market to a supply and demand based competitive one. The major goal of this reform is to promote energy conservation and alternative energy technologies, and to reduce oil and gas consumption through technology improvement and regulations (FERC, 2006). Under this restructure, a power system is separated to generation, transmission and distribution parts, which are major participants in an electricity market. In the current electricity market, these parts are typically highly related to individual companies, such as generation companies, transmission companies, and load serving entities. The market is also operated by organizations such as independent system operators. Brief introductions of the abovementioned players are listed below, according to Zhi Zhou (2010).

7.3.1 Generation Company

Power generation companies are the suppliers in the electricity market. In the wholesale market, generation companies compete with each other to sell their electricity through an auction market or bilateral contracts. Besides the decision on daily power generation schedule, power generation companies plan their generation capacity expansion and some potential issues coming out alone with it, for example, the CO_2 emission (Zhi Zhou, 2010).

7.3.2 Transmission Company

The restructure of the power system in the United States requires that the transmission systems be accessible to all suppliers (FERC, 2006). This requirement has brought the transmission systems into commercial operations. A transmission company is an organization that owns, maintains, and operates transmission assets for profit, but under regulation. It can propose and build new transmission facilities. In a deregulated market, a transmission company supplies reliable transmission rights to transport the electric power to destination area. Because the operation of transmission networks tends to suffer from monopoly, these transmission companies are less deregulated than generation companies (Zhi Zhou, 2010).

7.3.3 Load Serving Entity (LSE)

An LSE is the customer in a wholesale market and the supplier in a retail market, distributing electric service to end-users. Major activities of an LSE include forecasting the electricity demand in its service area and making contracts with other market participants to purchase electricity for satisfying the demand. This kind of LSE is called competitive retailers (CRs), who have to compete with other CRs to gain more customers because customers can switch among different CRs. In addition to CRs, at the current deregulated stage, there is another kind of LSE called non-opt-in entities (NOIEs), who are municipally owned utilities. NOIEs do not offer choices for customers (Zhi Zhou, 2010).

7.3.4 Independent System Operator (ISO)

An ISO is an organization that coordinates, controls, and monitors the operations of an electric power system in its service area. It is formed at the direction or recommendation of the FERC. There could be one ISO monitoring a single state, for example, the New York Independent System Operator (NYISO), or one ISO operating multiple states, such as the ISO-New England (Zhi Zhou, 2010).

7.4 A Building-Grid Interaction Framework

Given the background of building stocks and the electricity power market, we develop a framework that connects both the suppliers and consumers to evaluate the energy interaction between building stocks and the grid.

First of all, sets of input parameters for each prototypical building with respect to climate zone and vintage are stored in a database. When the total floor area, building vintage, and primary heating source (electricity or non-electricity) are specified for each building agent, the model selects the corresponding input files from the prototypical-building database and the right climate data from the climate database. Input data files then go to the simple hourly model. The calculated hourly electricity demands of building agents are then aggregated to derive the total hourly demand profile of the region.

Second, since building agents are based on bottom-up physical models, building operation behavior can be connected with the price aspects of the power market. First, building agent input parameters can be dynamically manipulated to reflect the reactions of building operation (e.g., change A/C set-point temperature, reduce lighting intensity) to the electricity price. This quantifies the amount of utility savings to the agents in a typical local climate condition. Second, in a real-time pricing market, the hourly electricity price can be determined by the building-stock electricity demand and power supply conditions.

Third, the level of competition in a wholesale market can lead to different electricity prices. If the competition is perfect, electricity prices are equal to the marginal cost for generation companies to generate electricity. This pricing phenomenon is illustrated in Figure 57.

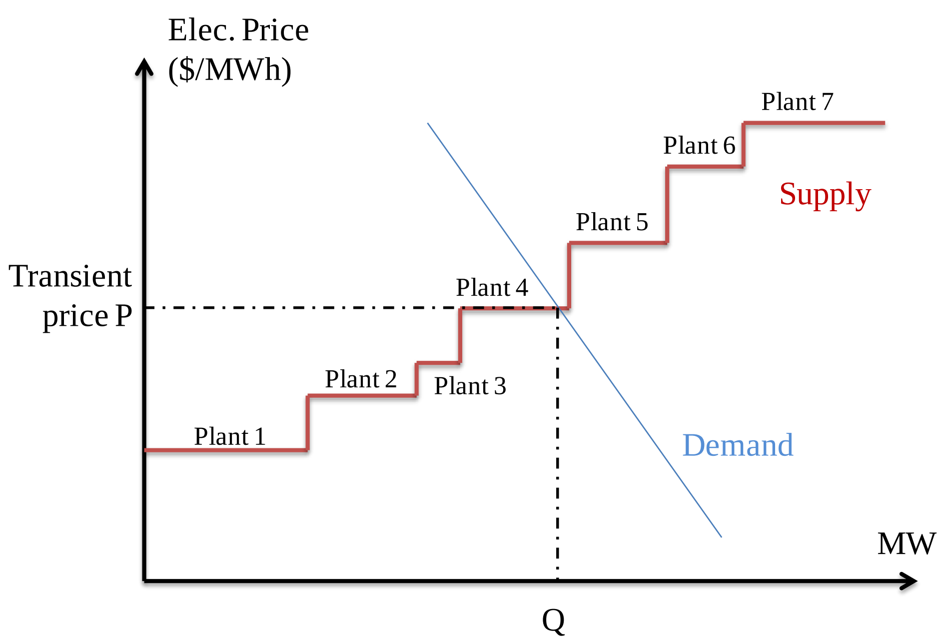


Figure 57 Schematic of electricity pricing in a perfect-competition market

In a perfect competition market, given the demand profile and a power supply curve, the electricity price can then be determined and inform building operations as a feedback. This calculation process is illustrated in Figure 58.

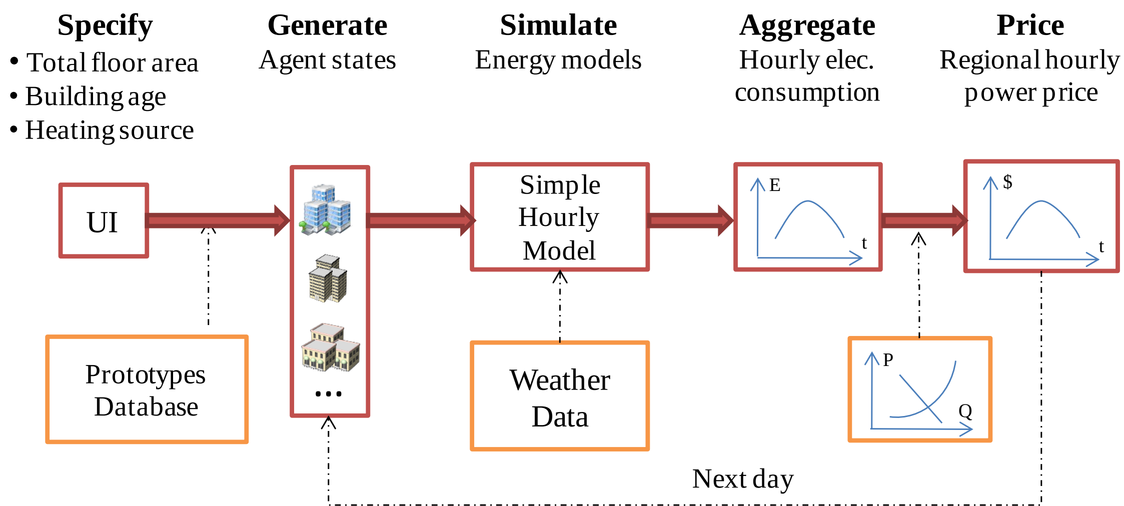


Figure 58 Framework of building stock DR analysis in a perfect-competition market

In an electricity market with imperfect competition among generation companies, electricity prices cannot be estimated without appropriately modeling the behaviors of generation companies in the auction market. A more complex pricing mechanism can be implemented in the ABMS platform. This market can be illustrated as Figure 59, which has a different market pricing module from the perfect-competition market in Figure 58.

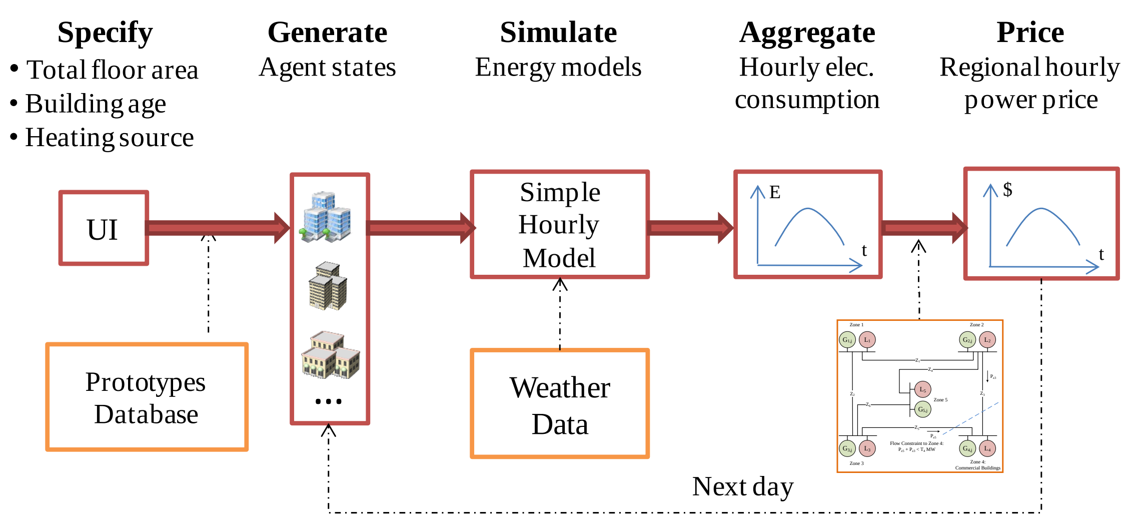


Figure 59 Framework of building stock DR analysis in an imperfect-competition market

7.5 Modeling Demand Response from Building Stocks

7.5.1 Agent Behavior 1: Load Reduction

Three load reduction behaviors can be triggered by utility price signals. Agents can be triggered to: (1) increase/decrease the AC set-point temperature for cooling/heating by a certain number of degrees; (2) reduce lighting power by a certain percentage or to a certain energy use intensity level (in W/m^2); and (3) reduce internal equipment power by a certain percentage or to a certain energy use intensity level (in W/m^2). Every building agent, even those connected to the same transmission bus or being of the same building type, may have different thresholds at which load reduction behaviors will be triggered. A generic comparison between scenarios with and without load reduction is illustrated in Figure 60, which shows when the electricity price goes up to certain threshold, load reduction actions are triggered.

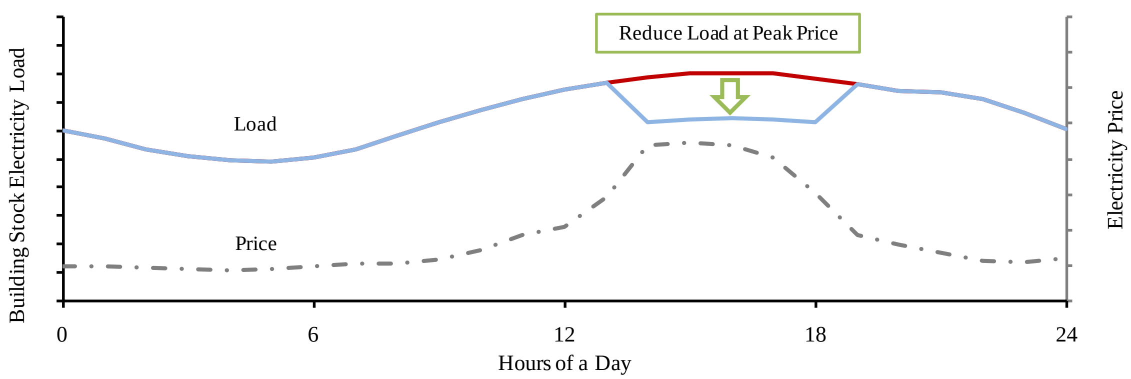


Figure 60 Agent Behavior 1: Load Reduction

7.5.2 Agent Behavior 2: Load Shifting without Energy Storage

By default, each building agent has a set of typical operation schedules for occupancy, lighting, HVAC, and internal/external equipment. In the model, these schedules may be adjusted or modified so that different load-shifting scenarios (i.e., moving energy-intensive activities to off-peak hours) may be simulated. This process is illustrated in Figure 61.

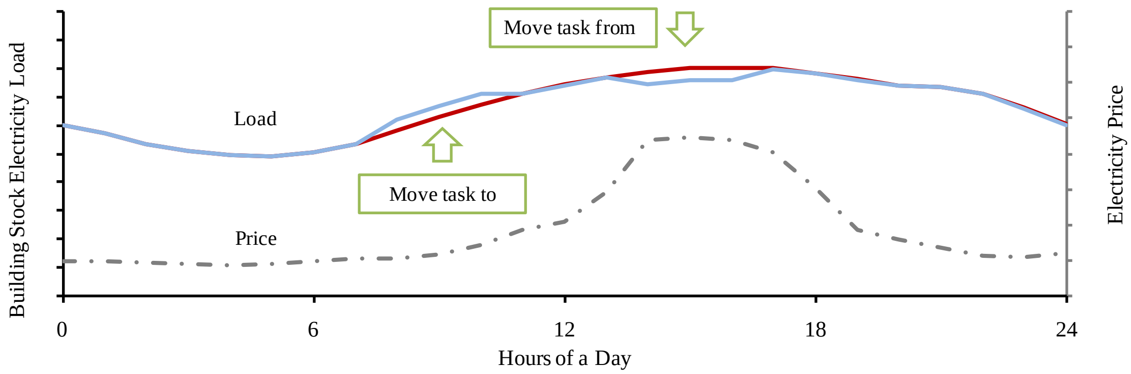


Figure 61 Agent Behavior 2: Load Shifting without Energy Storage

7.5.3 Agent Behavior 3: Load Shifting with Energy Storage

In addition to the above two types of demand response, energy storage for buildings can also be simulated. For electric energy storage, the user needs to specify the parameters—such as battery storage capacity, charge-discharge cycle efficiency, percentage of buildings in the stock using storage, and the schedule to use the stored energy—for each agent. Next, the calculated building electricity load profile will be adjusted accordingly. For thermal storage (and similar to the case with electric storage), users are able to specify the properties of the system and make relevant changes to the model. Taking electric energy storage as an example, the battery charging and discharging process for a generic day is illustrated in Figure 62.

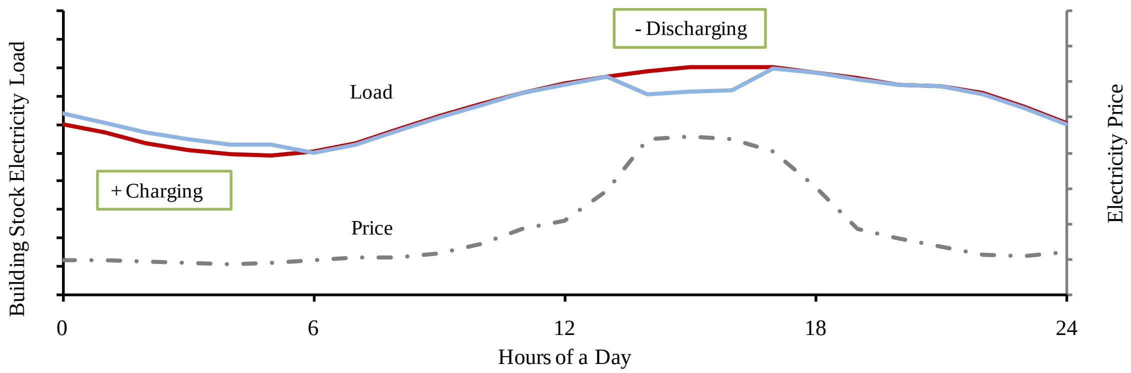


Figure 62 Agent Behavior 3: Load Shifting with Energy Storage

These three types of agent behaviors will be implemented in the short-term model and tested in this study. In addition to the proposed physical model, market pricing algorithms can be coupled with this model to determine the resulting hourly electricity prices and costs. A simple supply-demand-curve pricing algorithm will be used in the test case.

7.6 ABMS Implementation

In this study, a cluster of buildings of the same type (use the same prototypical model) within the same region (use the same weather data) are considered as one agent (i.e., stock). It is thus represented by one prototypical building energy model, whose specifications are determined by the characteristics of buildings in this stock. The total energy use of this agent (i.e., building stock) is estimated by multiplying the energy use per floor area of the selected prototypical model with the total gross floor area of all the buildings in this stock. Different agent adaptive actions, short-term (e.g., demand response) or long-term (e.g., degradation and retrofit), can be simulated by changing variables of the prototypical models for the agents. Figure 63 is the UML state diagram that illustrates actions of building stock agents in the short-term application.

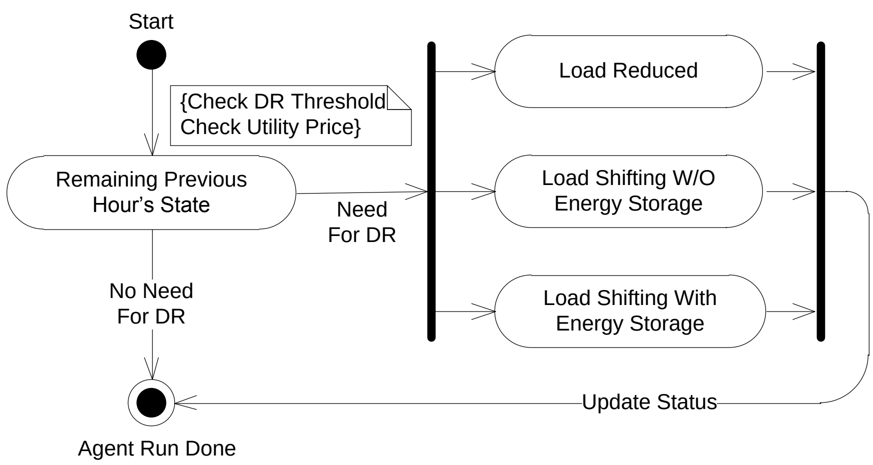


Figure 63 UML state diagram for the building agent in the short-term analysis

This development philosophy allows flexibility in model components and scalability potential to avoid the need to restructure the model in major ways when additional detail or complexity is added.

7.7 Test Cases under Perfect Competition

In this proposed framework, since building agents are based on bottom-up physical models, building operation behavior can be connected with the price aspects of the power market. First, building agent input parameters can be dynamically manipulated to reflect the reactions of building operation (e.g., change A/C set-point temperature, reduce lighting intensity) to the electricity price. This quantifies the amount of utility savings to the agents in a typical local climate condition. Second, in a real-time pricing electricity market, the hourly electricity price can be determined by the building stock load profile and a power supply curve. This demand response process is also modeled in the prototype. This section shows three test cases to demonstrate these scenarios.

7.7.1 Test Case 1: Load Reduction

We use a simple building stock consisting of only office buildings to demonstrate the demand reduction. Specifications of the building agent in this test case are shown in Table 22.

Table 22 Building stock specification in Case 1

Building Type	Total Floor Area (million sq. m)	Dominant Building Age	Primary Heating Source
Office	1	Pre-1980	Natural gas

This building stock is located in Chicago. A typical hourly electricity price profile in Illinois is assigned to the agent (Figure 64). It is assumed that the electricity demand of this agent has little impact on the electricity price.

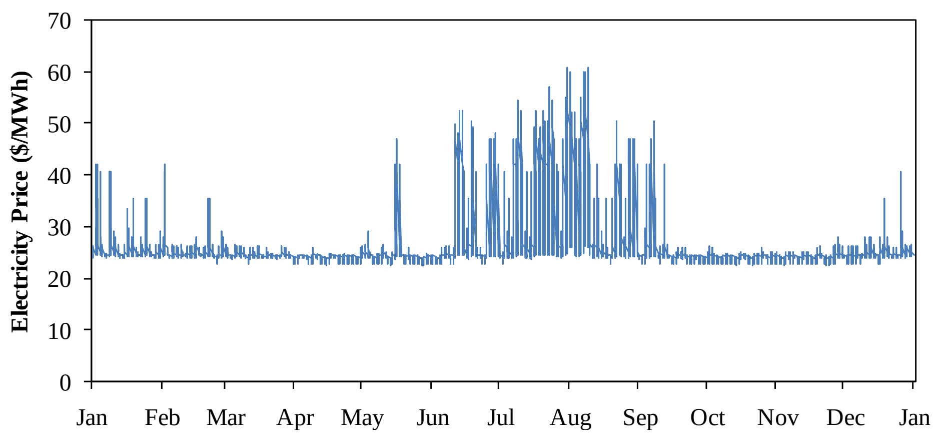


Figure 64 Typical hourly electricity price profile

In this market, given the electricity price in the previous hour, it is assumed that buildings can take three demand-reducing actions listed in Table 23. When the price is above \$45/MWh, the indoor set-point temperature is increased by 2°C. When the price is above \$50/MWh and \$55/MWh, lighting and internal equipment power, respectively, decrease by 20%.

Table 23 Agent load-reducing actions and electricity price

Demand Reduction Scenario	When the Power Price Is above	Action from Buildings
Cooling set-point	\$45/MWh	Increase set-point temp. by 2℃
Lighting	\$50/MWh	Reduce lighting load by 20%
Internal equipment	\$55/MWh	Reduce load by 20%

On the basis of TMY climate data and stock specifications, the prototype simulates hourly stock electricity demand and price for a year. Figure 65 compares the baseline (no action) and reduced loads simulated for the week of August 4. At noon of each business day when the electricity price approaches the daily peak, three load reduction scenarios are activated to reduce the power demand. The corresponding hourly electricity cost is also plotted in Figure 66.

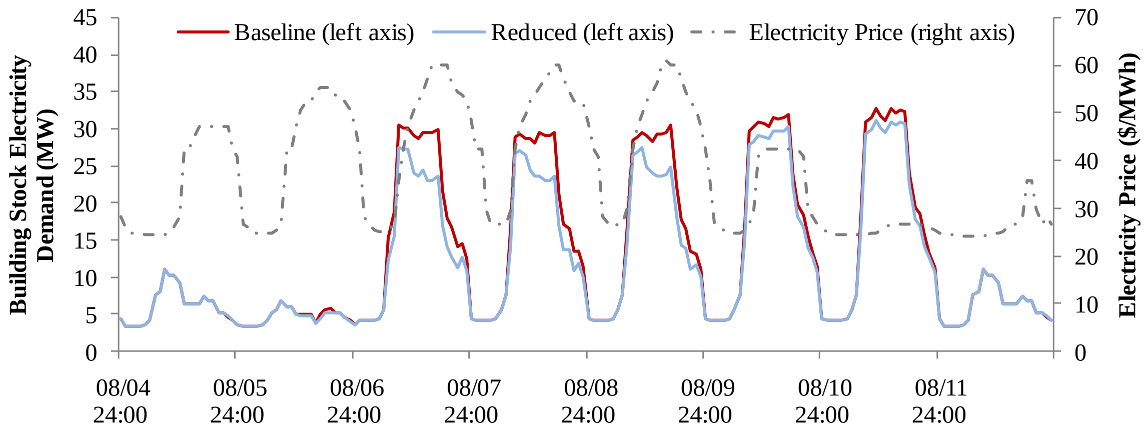


Figure 65 Office agent electricity demand profile before and after three reduction actions, Aug. 4th through 12th

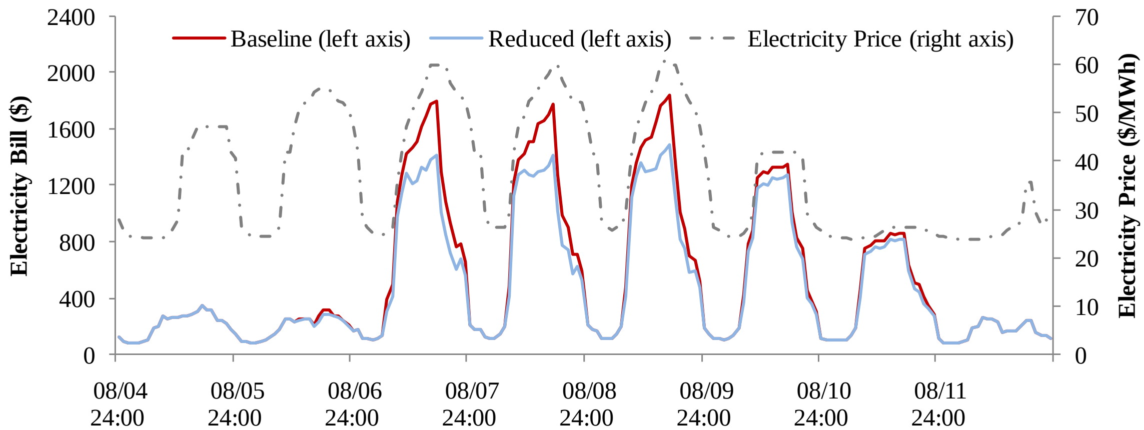


Figure 66 Office agent electricity bill profile before and after three reduction actions, Aug. 4th through 12th

To quantify the effectiveness of the different load reduction scenarios, the annual electricity conservation and utility savings are aggregated (Table 24). In this test case, reductions in lighting and internal equipment power have very little impact with regard to saving energy and money because of the higher thresholds and small reduction percentages for these two scenarios. But increasing the 2℃ cooling set-point temperature at an electricity price of $45/MWh or above leads to a 2.83% annual electricity reduction and 3.41% monetary savings.

Table 24 Utility savings of the demand reduction actions for the test building stock

Demand Reduction Scenario	Annual Electricity Reduced (MWh | %)		Annual Monitory Saving ($ | %)	
(a) Cooling set-point temp.	2,733	2.83%	93,707	3.41%
(b) Lighting	231	0.24%	12,163	0.44%
(c) Internal equipment	44	0.05%	2,549	0.09%
(a), (b), and (c)	3,009	3.11%	108,418	3.95%

7.7.2 Test Case 2: Grid Reaction

Test Case 1 showed an example of estimating energy and monetary savings of load reduction when the electricity price profile is fixed. If we consider a city/state-scale network in the real-time electricity market, the electricity price can also change when buildings reduce their peak loads. A much larger building stock with a combination of different building types (Table 25) is modeled in this test case. The relative proportion of each type is estimated according to the CBECS 2003 building characteristics summary for the Midwest U.S.

Table 25 Building stock specification in Test Case 2

Building Type	Total Floor Area (million sq. m)	Dominant Building Age	Primary Heating Source
Office	108	Pre-1980	Natural gas
Supermarket	14	Post-1980	Natural gas
Strip Mall	11	Post-1980	Electricity
Education	92	Pre-1980	Natural gas
Healthcare	29	Post-1980	Natural gas
Warehouse and Storage	109	Post-1980	Natural gas
Lodging	41	Pre-1980	Electricity
Food Service	16	Post-1980	Natural gas
Retail (other than mall)	32	Post-1980	Natural gas
Food Sales	12	Post-1980	Natural gas

We consider a macro-model of the electricity market, a black box that abstracts the market mechanism and trading, and the transmission power flow security involved in an actual electricity market. Given the characteristics of the market, our prototype gives the market prices based on the economics of supply and demand, shown in Figure 67. The supply curve is generated from the capacity of the local generation companies. In each hour, the electricity price is determined by this supply curve and the total electricity demand of the previous hour.

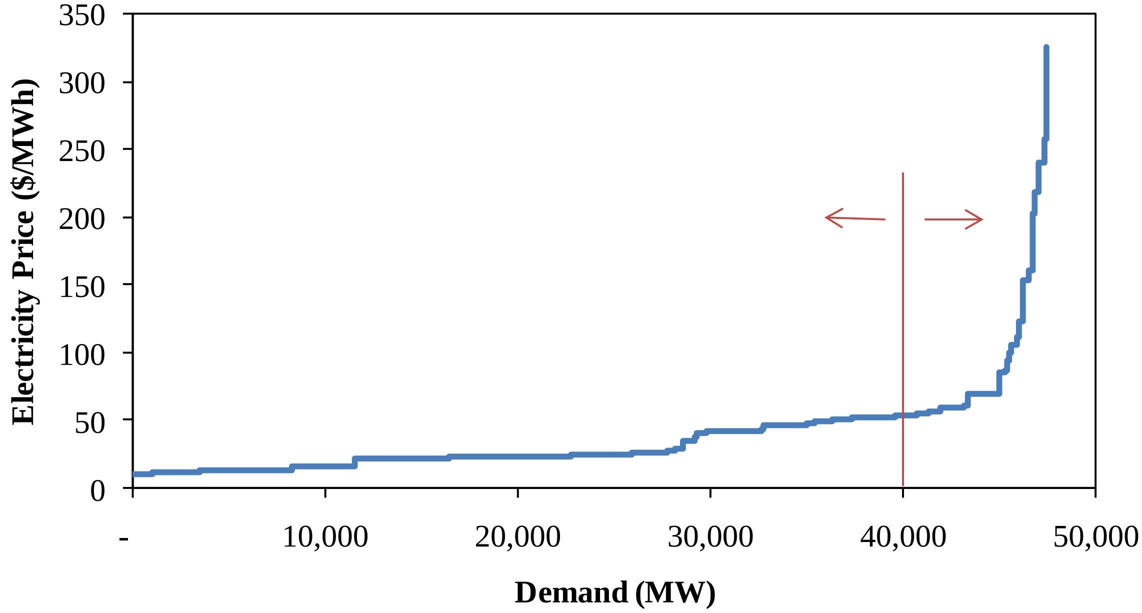


Figure 67 Sample electricity supply curve

Since the commercial sector is not the only electricity consumer, we assume that the residential, industrial, and transportation sectors in total consume 65% of the total regional electricity (U.S. EIA, 2009a). This portion is modeled as a fixed base demand curve below the fluctuating demand of commercial buildings. For the baseline case in which no building agent takes demand reduction actions, the regional electricity demand profile is calculated as shown in Figure 68.

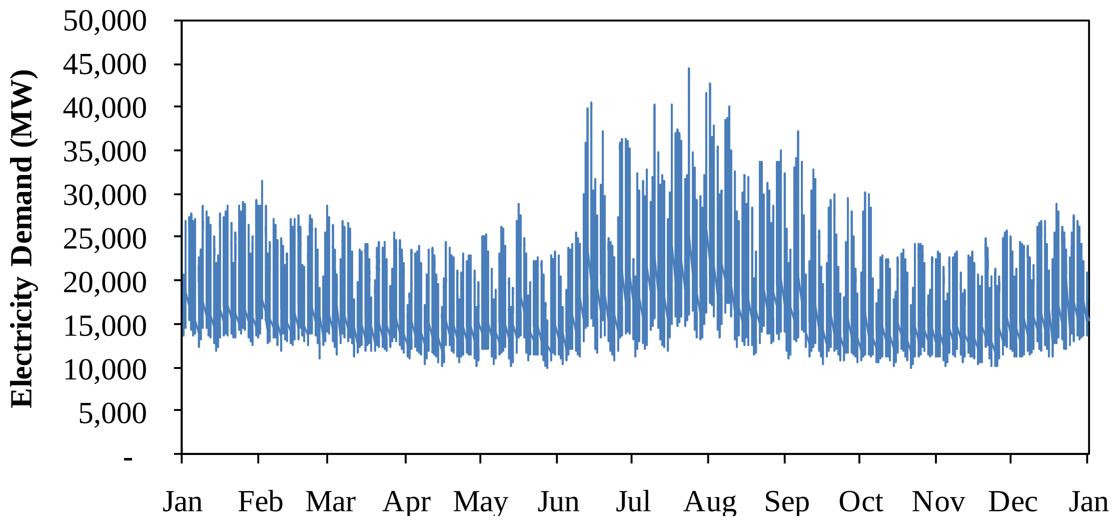


Figure 68 Estimated electricity load profile baseline

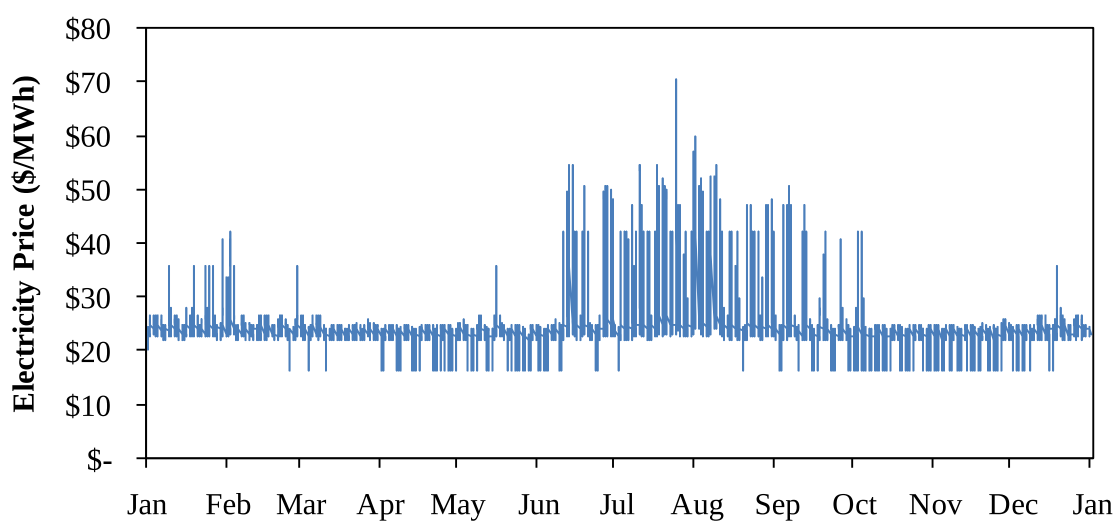


Figure 69 Estimated electricity price profile baseline

In this case, the load reduction actions are applied to more building types. The example set of arrangements is listed in Table 26.

Table 26 Agent load-reducing actions and electricity price

Demand Reduction Scenario	Agents Applied to	When the Power Price Is above	Action from Buildings
(a) Cooling set-point temperature	O, H, R, FE	$45/MWh	Increase set-point temp. by 2℃
(b) Heating set-point temperature	O, H, R, FE	$45/MWh	Decrease set-point by 2℃
(c) Lighting	O, S, R, E, FE	$45/MWh	Reduce lighting load by 30%
(d) Internal equipment	O, E	$45/MWh	Reduce internal equip. load by 30%

The simulation results are plotted in Figure 70, which compares the hourly load profile with and without load reduction actions. Small decreases in electricity demand appear during the middle of each day, when the electricity price is high. All the demand reduction actions have led to a decrease in annual regional electricity consumption (including all the sectors) of about 0.2%.

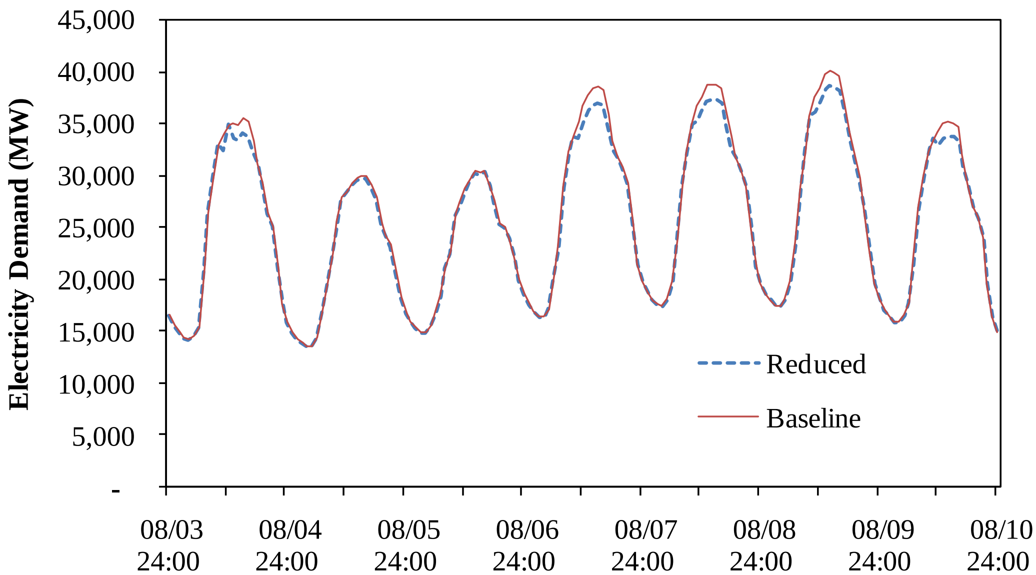


Figure 70 Commercial building stock electricity demand before and after reduction actions, Aug. 4th through 11th

However, on the price side, these actions shaved the electricity price profile (compare Figure 71 and Figure 69). The annual maximum market price dropped from ~$70 to ~$60/MWh. Although in this test case simulation, only part of the building agents took action, the changes in load and price profiles demonstrate the impact of commercial buildings on the smart grid.

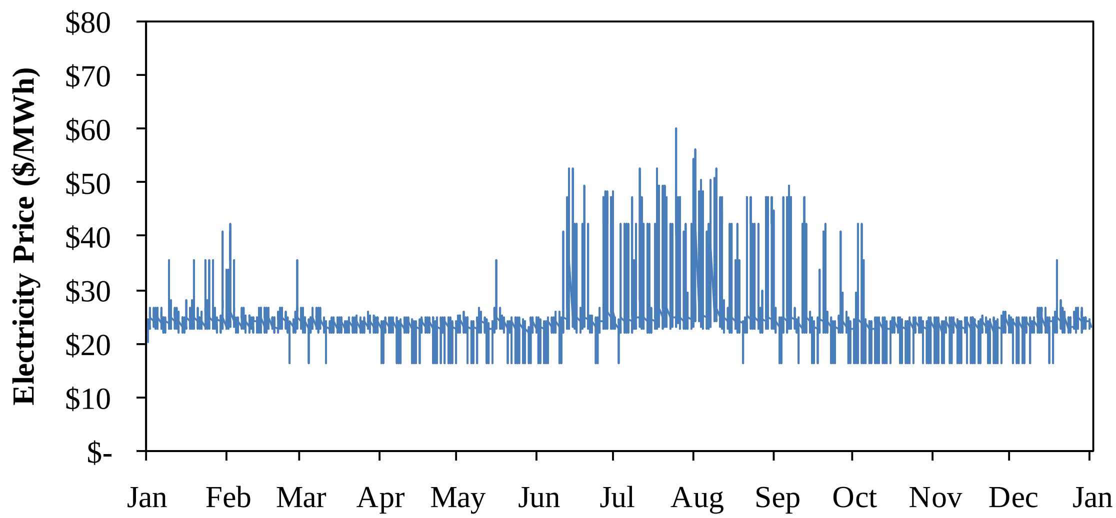


Figure 71 Estimated electricity price profile– after load reduction

7.8 Test Cases under Different Levels of Market Competition

In this scenario, we present an ABMS model for an electricity market that includes generation companies (GenCos), load-serving entities (LSEs), commercial building aggregators (CBAs), and an independent system operator (ISO), described in Section 7.3.

In the electricity market, GenCos bid on the basis of their own historical bids, winning quantities, and clearing prices. GenCos cannot know bidding strategies and winning quantities of each other. Nevertheless, obtaining this information is critical to enabling GenCos to make decisions on the next bid. Therefore, GenCos have to acquire the ability to learn to estimate the bidding strategies of their opponents and thereby make rational decisions. Meanwhile, GenCos' bidding behaviors can also be influenced by the demand of commercial buildings, which is sensitive to the market price. Hence, the objective of our study is to understand the consumption behaviors of commercial buildings in a real-time pricing environment under different market structures, with conditions ranging from that of a duopoly to perfect competition.

7.8.1 Power Market Model

To make the simulation close to the real-world model and reveal nontrivial results, an electricity market can be set up with comprehensive characteristics on physical transmission configuration, electricity supply, and end-use demand.

Transmission Network: The ABMS model is based on a given transmission network, where buses are connected by transmission lines with transmission capacity limits. GenCos, LSEs, and CBAs are located at different buses. The market prices are calculated based on the supply and demand conditions and the transmission network configuration.

Market Participants and Auction Procedure: In the simulated electricity market, GenCos, LSEs, CBAs, and the ISO correspond to suppliers, buyers, and the market operator, respectively. The CBAs aggregate the load from all of the buildings under their administration and purchase electricity to satisfy this demand. The GenCos compete with each other to sell their electricity. The ISO clears the market by minimizing the total production cost and determining the prices.

In the day-ahead auction market of our simulation model, CBA and LSEs estimate the load in their administrated areas for each hour of a day and submit that information to the ISO as bids. The GenCos decide their bids by using their knowledge about the environment and opponents. Before the beginning of Day t, the ISO closes the market for day t and clears the market by using a standard bid-based DC optimal power flow formulation (Zimmerman, Murillo-Sánchez, & Thomas, 2011). The ISO determines generation dispatch levels for each hour of day t to minimize generation operational costs subject to bus balance constraints, transmission line capacity constraints, and generation operating capacity constraints. For each hour of Day t, a locational marginal price (LMP) is determined at each bus as the shadow price for the balance constraint at this bus; this is the price paid to GenCos for power injections at this bus and paid by LSEs for power withdrawals at this bus during each hour. On Day t, the GenCos schedule their operations and generate the accepted amount of electricity that was bid on and settled the day before (i.e., on Day $t-1$). The LSEs and CBAs receive the amount of electricity they intended to buy and distribute it to their end customers.

Market Agents: Our model implements four types of agents corresponding to the four participants in the market: GenCo agents, LSE agents, CBA agents, and the ISO agent.

GenCo Agents: Each GenCo has only one generator represented as a generator agent. GenCo agents are differentiated by their capacities and cost functions. The cost function is modeled as a polynomial cost function, which is defined in the following equation:

$$C_j(q_j) = a_{j0}q_j^2 + b_{j0}q_j + c_{j0},\ q_j \in [0, \Phi_j] \qquad (7\text{-}1)$$

where Φ_j is the capacity; q_j is the amount of electricity supplied by GenCo G_j; $C_j(q_j)$ is the cost for G_j to supply q_j units of electricity; and a_{j0}, b_{j0}, and c_{j0} are three coefficients of the cost function.

When a GenCo agent submits its bid to the ISO agent, it is required to report its cost function. If the GenCo agent reports its marginal cost function, it is called the marginal cost bidder. Another situation is that the GenCo agent can report an adjusted cost function (although it is still assumed the "marginal" cost function from the ISO's side). In this case, the agent tries to make more profit by bidding strategically. If the GenCo agent has market power, its objective could be maximizing its profit from this adjustment.

Because the price is decided by the GenCo's cost function, a price adjustment is implemented by raising or dropping the coefficients of the cost function, which is reported to the ISO as the cost function. The adjustment is represented by the markup rate compared with the coefficients of the true cost function, which is defined by the following equation:

$$S_j(q_j) = a_{j0}m_jq_j^2 + b_{j0}m_jq_j + c_{j0}, \qquad q_j \in [0, \Phi_j] \qquad (7\text{-}2)$$

where $S_j(q_j)$ is the cost function reported to the ISO and m_j is the markup rate, and $m_j \geq 1$. For example, if a GenCo bids at a rate 120% higher than its marginal cost, its markup rate is 2.2. If it bids at the true cost, its markup rate is 1.

LSE Agents: The agent forecasts the load for the next day and reports it to the ISO agent as its demand. It does not take strategic actions.

CBA Agents: Each CBA agent has its unique load reduction actions. An electricity price threshold is assumed at which CBA agents will become triggered to take actions. For example, if the market price is higher than the price threshold, the CBA agents can choose to turn off some pieces of equipment to reduce the energy consumption. In this study, CBAs can perform any combination of the following actions: turn off lighting by a certain percentage, turn off pieces of plugged equipment by a certain percentage, and set cooling (air-conditioning) or heating set-points higher (lower) by certain degrees. It is assumed in the day-ahead market that, at the beginning of each day, CBAs refer to the price from seven days ago to make DR decisions, because the load profile is similar to the one that occurred a week ago.

ISO Agents: The objective of the ISO is to regulate the market by minimizing the total production cost in the market. The ISO agent selects the least expensive generators with a higher priority. The constraints associated with the cost minimization problem by the ISO include unit capacity, transmission line capacity, etc. The ISO agent collects bids from the GenCos, LSEs, and CBA agents before the market is closed. Then, it clears the market by solving an optimal power flow problem. After the market is cleared, the ISO agent informs the GenCos, LSEs, and CBA agents of their generation schedule.

7.8.2 Market Structures

In an electricity market characterized by perfect competition, all GenCo agents are price takers who bid their true production costs into the market. If the market has only one GenCo with dominant market power and can manipulate market prices, it is a monopoly market. If there are two GenCos, it is a duopoly market. Given the system load, the market price is lowest in a perfect competition market and highest in a monopoly market.

7.8.3 Learning Model for GenCo Agents

Learning Model: We use the Roth-Erev reinforcement learning algorithm (Erev & Roth, 1998; Sun & Tesfatsion, 2007) to model the GenCos' strategic bidding behaviors. The intuition is that a GenCo agent selects a bidding action from its action alternatives at each round on the basis of feedback (i.e., the quantity of scheduled output and market price) from the historical round. The agent then updates the propensity of its bid options thereafter. Table 27 lists the notation used in this section.

Table 27 Notation used in this section

i	The i^{th} GenCo, $i = 1,2,\ldots,N$
j	The j^{th} bidding action option, $j = 1,2,\ldots,M$
t	The t^{th} day, $t \in \mathbb{N}$
h	The h^{th} hour, $h = 1,2,\ldots,24$
$a_{i,j}(t,h)$	The j^{th} action of GenCo i
$q_{i,j}(t,h)$	The i^{th} GenCo's propensity value for its j^{th} action at hour h on day t
$p_{i,j}(t,h)$	The i^{th} GenCo's probability value to select its j^{th} action at hour h on day t
α_h	Forgetting rate at hour h which slowly reduces the importance of past experience
ϵ	Experimentation/Generalization rate to quantify how much the agent will adapt from current experience
K	Maximum experiment days
M	Total number of actions

The simulation is initialized following two steps:

1) For each GenCo Agent i, for each of its action j, $q_{i,j}(0,0) = 0$ and $p_{i,j}(0,0) = 1/M$;

2) Initialize simulation coefficients α, ϵ, and K.

After the initialization, for each day (Day $t = 1,2, \ldots, K$), four steps below are applied to each GenCo Agent i:

1) Randomly select a bidding action for each hour h of Day t according to the selection probability:

$$p_i(t,h) = p_{i,1}(t,h), p_{i,2}(t,h), \ldots, p_{i,M}(t,h) \quad (7\text{-}3)$$

2) Calculate rewards (profit) $r_i(t,h)$;

3) Update the propensities for its actions for each hour h of the next day:

$$q_{i,j}(t+1,h) = \begin{cases} (1-\alpha_h) \times q_{i,j}(t,h) + r(t,h) \times (1-\epsilon), if\ j = k \\ (1-\alpha_h) \times q_{i,j}(t,h) + r(t,h) \times \left(\frac{\epsilon}{M-1}\right), if\ j \neq k \end{cases} \quad (7\text{-}4)$$

4) Update the strategy $p_i(t,h)$ for each hour h of the next day:

$$p_{i,j}(t+1,h) = \frac{e^{q_{i,j}(t,h)/(K-t)}}{\sum_{j=1}^{M} e^{q_{i,j}(t,h)/(K-t)}} \quad (7\text{-}5)$$

7.8.4 Numerical Analysis

To simulate the commercial building DR under different market structures, we use a five-zone transmission network, as illustrated in Figure 72. Each zone has one LSE, except in Zone 4. Zone 4 has multiple CBA agents. These zones are interconnected through six transmission lines with capacity limits. In Figure 72, $G_{i,j}$ represents the j^{th} generator in the i^{th} node, L_i the load in the i^{th} node, and Z_i the impedance of the i^{th} node.

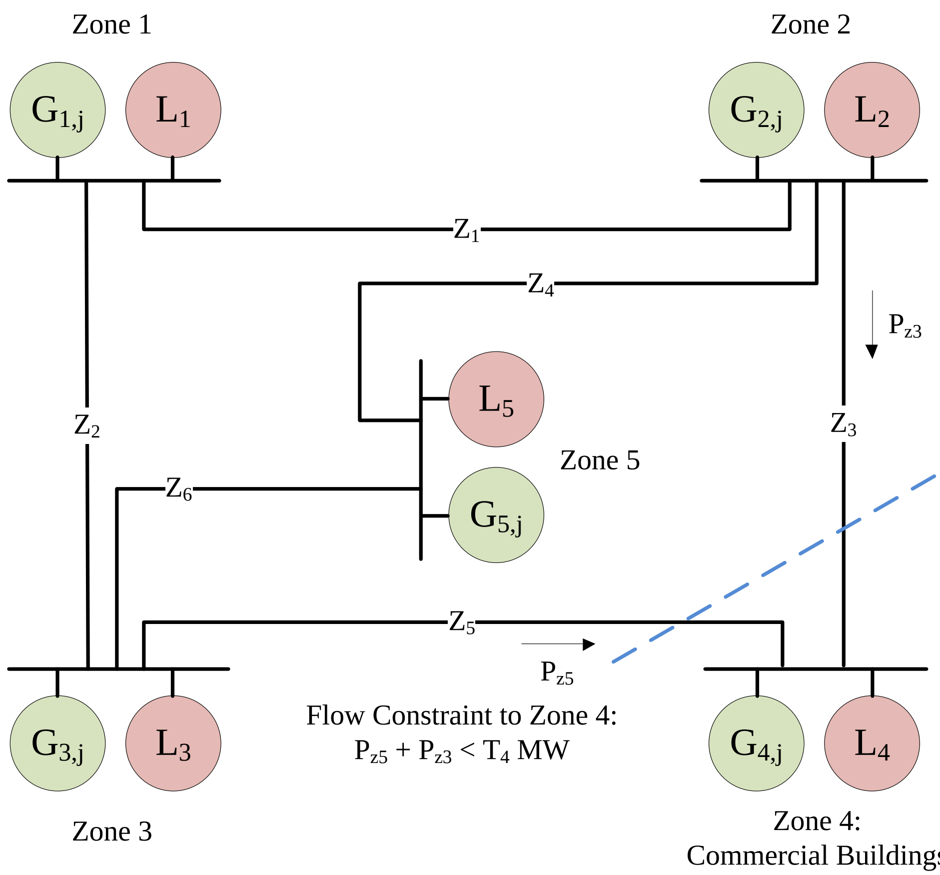


Figure 72 An experimental five-zone power system

On the supply side, each zone has one GenCo agent, except Zone 4. In Zone 4, there are six GenCo agents, denoted by $G_{4,j}(j = 1, \ldots, 6)$. Compared with the generators in Zone 4, other GenCos have cheaper production costs and can supply the demand in Zone 4 after satisfying demand in their own zones. However, the amount of electricity exported to Zone 4 is limited by the transmission line capacity, which is denoted by T_4. Among the six GenCos in Zone 4, two (i.e., $G_{4,1}$ and $G_{4,2}$) are giant companies with identical generation capacity, the sum of which is larger than the sum of the capacities of the other four small generators, whose capacities are also identical. These four smaller GenCos are price takers who do not bid strategically. In contrast, $G_{4,1}$ and $G_{4,2}$ can use different pricing strategies to make greater profits. If these two GenCos still bid at their marginal cost, the market becomes a perfect competition market. If they bid more strategically, the market is a duopoly market since other GenCos are price takers. On the demand side, the loads in Zones 1, 2, 3, and 5 (i.e., L_1, L_2, L_3, and L_5) are non-price-responsive. Because we are investigating the impact of DR from commercial buildings, we simplify the demand profiles from other sectors as shown in Figure 73. In Zone 4, however, there are multiple types of CBAs with different design and operation specifications (listed in Table 28). Each of these CBAs is able to perform load reduction strategies that are triggered by pre-defined electricity prices and are independent of other building agents. We assume that building agents make their decisions based on the electricity price of the same hour in the previous week.

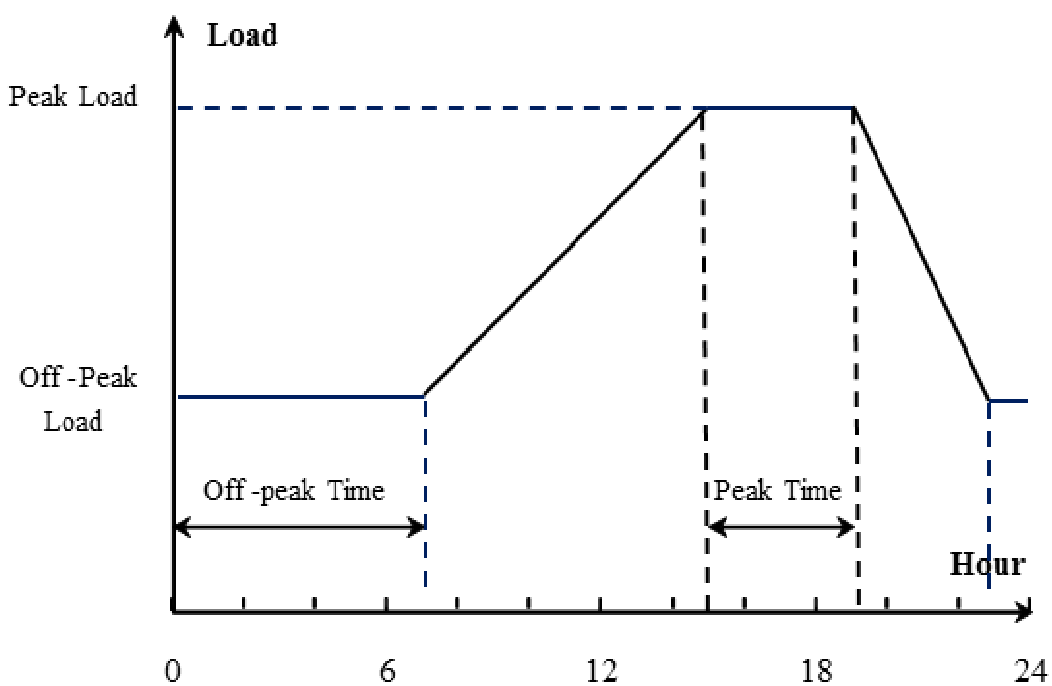


Figure 73 Schematic hourly load profile for non-DR loads

Table 28 Empirical commercial building agents specifications

Building Type	Floor Area (million m^2)	Dominant Building Age	Primary Heating Source
Office	22	Pre-1980	Natural Gas
Supermarket	3	New Construction	Natural Gas
Strip Mall	2	Post-1980	Electricity
Education	18	Pre-1980	Natural Gas
Healthcare	6	Post-1980	Natural Gas
Warehouse	22	Post-1980	Natural Gas
Lodging	8	Pre-1980	Electricity
Food Service	3	Post-1980	Natural Gas
Retail	6	Post-1980	Natural Gas
Food Sales	2	Post-1980	Natural Gas

Different levels of DR participation from buildings result in different energy and monetary costs. Hence, two scenarios with different participation levels are being tested in this numerical analysis: the small scale (only offices perform DR) and large scale (all building types perform DR) case. Detailed settings related to the power system are listed in Table 29 and Table 30.

Table 29 Initial bus data in the test case

Bus #	Type	Peak delivered elec. (MW)	Generation Capacity (MW)	Voltage (p.u.)	Base (kV)	Max Voltage (u/p.u.)
1	Reference	500	1500	1	345	1.05
2	PV	1000	1500	1	345	1.05
3	PV	1000	1500	1	345	1.05
4	PV	Responsive	11000	1	345	1.05
5	PV	200	1500	1	345	1.05

Table 30 Initial data of transmission lines

Branch	From	To	r	x	b	Flow Limit (MW)
1	1	2	0.00132	0.02020	1.47250	3000
2	1	3	0.00197	0.03920	2.19000	3000
3	2	4	0.00161	0.01664	1.07800	3000
4	2	5	0.00064	0.00883	0.59300	3000
5	3	4	0.00070	0.00850	0.14800	3000
6	3	5	0.00140	0.01830	0.28310	3000

7.8.5 Small-Scale DR: Office Only

To limit the variables in the experiment, we assume that only office buildings in Zone 4 perform load reduction during peak hours in this test case, while the other types of buildings in Zone 4 maintain their individual load profiles irrespective of electricity prices. The DR actions include adjusting the power intensity of lighting and plug equipment, as well as the set-point temperatures of cooling and heating units. According to the electricity price seven days ago, when the electricity price of an hour reaches a certain threshold, the building agent starts to take one or multiple actions to reduce the demand. In this case, we are simulating the situation in which only one type of building (namely, office buildings), is capable of performing DR. Thresholds of the office agents are illustrated in Figure 74.

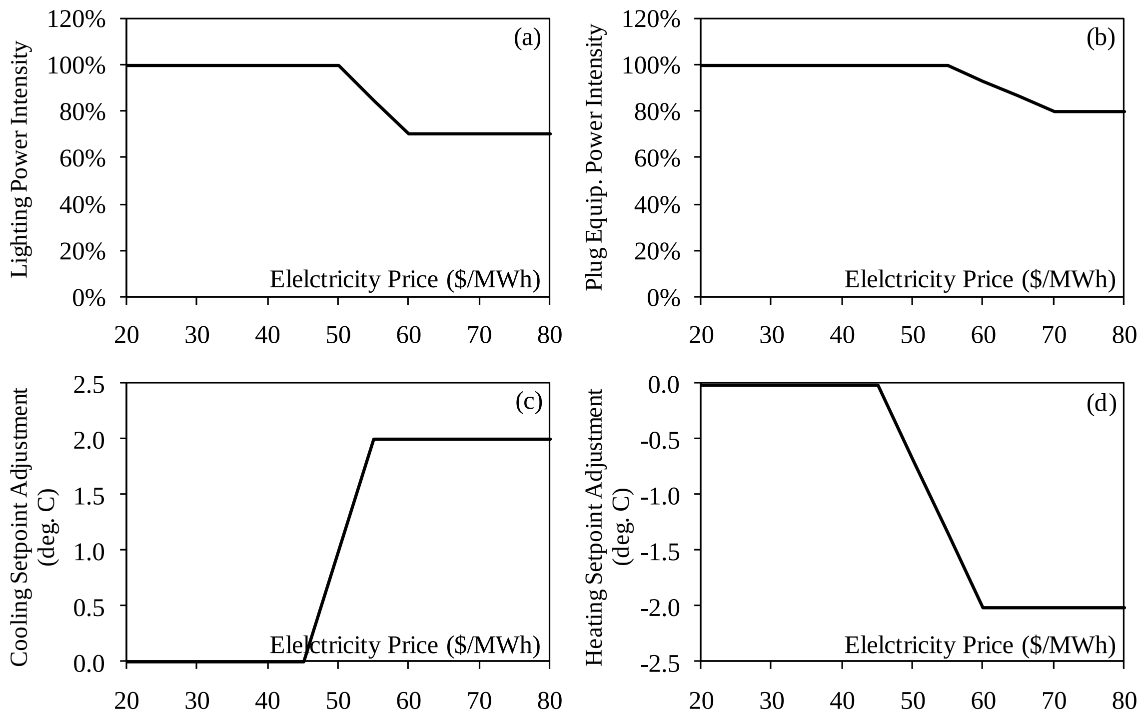


Figure 74 Office stock DR actions and price thresholds

In Figure 74, (a) and (b) are power intensity adjustment for lighting and plug Equipment; (c) and (d) are set-point temperature adjustment for cooling and heating.

The simulation has been performed for a typical meteorological year to generate the hourly electricity loads of office buildings and the electricity prices under different levels of market competition. The results indicate that under perfect market competition, as shown in Figure 75, the building load profile is shaved in comparison to the peak hours of a week ago.

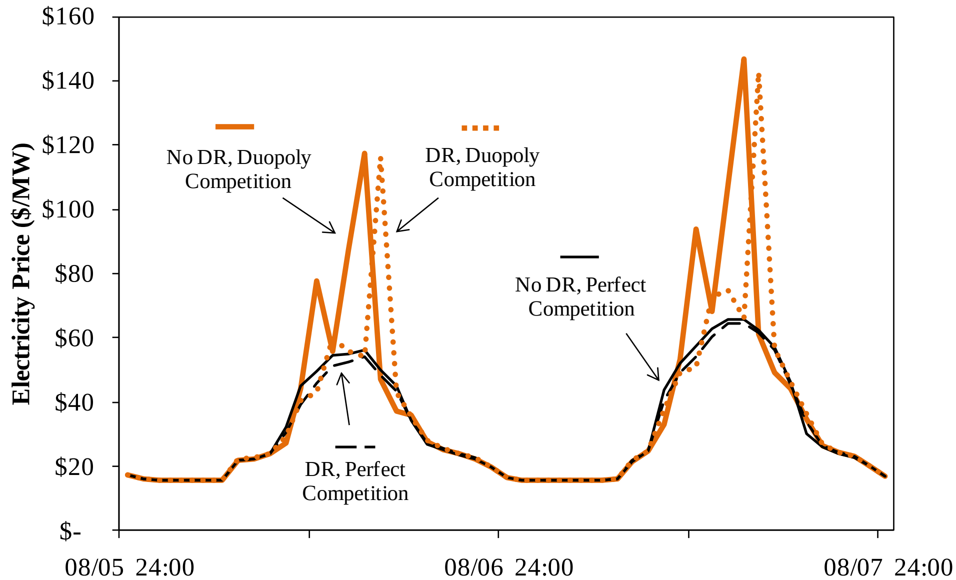


Figure 75 Electricity prices under different market competition levels with only office buildings performing DR during Aug 5–6

In Figure 75, we compare the electricity prices without and with demand response in two different market competitions. Since the patterns are similar every day, we only demonstrate results of two days in Figure 75. One observation from the result is that electricity prices in perfect competition scenarios are relatively close to each other, which indicates that there is no significant impact on market prices under the perfect competition scenario if only a small representation of building types (offices) performs DR. However, if the market is under duopoly competition, electricity prices are much higher than they are under the other two situations because of the imperfect nature of the market competition.

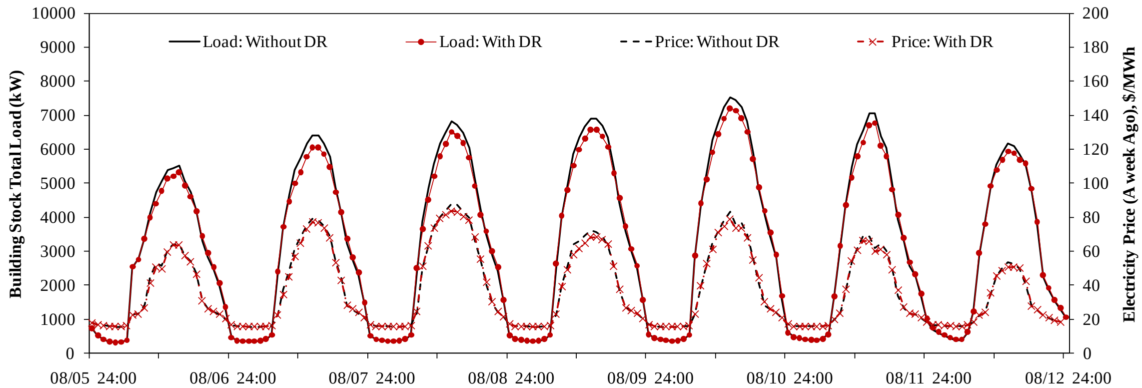


Figure 76 Building stock total load with and without office DR under perfect market competition during August 5–11

To evaluate the overall consequence of DR as practiced by office buildings, the standard deviation (StdDev) and summation (Sum) of the results are calculated to compare different scenarios. For the electricity price, standard deviation is reduced by 2.9% in a perfect competition market when office buildings perform DR actions, which indicates a lower volatility of the market. However, in scenario (3), the standard deviation of the electricity price increases by 66.7% compared to the baseline. Because of the high prices in scenario (3), total electricity consumption of buildings in scenario (3) is 2.0% lower than it is in the baseline, and is reduced by only 1.8% in scenario (2). As an overall impact of prices and consumption, the office stock electricity cost in scenario (2) is 2.5% lower than that of the baseline. However, buildings spend more than 18% for the electricity bill under the duopoly market as compared with the baseline.

Table 31 Comparison of electricity price, consumption, and cost under different Market structures (Small-Scale DR)

Outputs under Four Scenario	StdDev	Sum	Reduction[6]
Price ($/MWh)			
(1) No DR, Duopoly	39.5	N/A	-101.6%
(2) No DR, Perfect	19.6	N/A	0
(3) DR, Duopoly	32.6	N/A	-66.7%
(4) DR, Perfect	19.0	N/A	2.9%
Consumption (MWh)			
(1) No DR, Duopoly	N/A	2,205	0
(2) No DR, Perfect	N/A	2,205	0
(3) DR, Duopoly	N/A	2,162	2.0%
(4) DR, Perfect	N/A	2,165	1.8%
Cost ($M)			
(1) No DR, Duopoly	N/A	139.1	-36.0%
(2) No DR, Perfect	N/A	102.3	0
(3) DR, Duopoly	N/A	121.4	-18.7%
(4) DR, Perfect	N/A	99.7	2.5%

Results of this test case indicate that under perfect market competition, DR from a small-scale representation of buildings does not significantly impact electricity market prices. In addition, small scale of DR behavior does not result in recognizable energy and cost conservation for the buildings with price-responsive demand. However, if the market competition is imperfect, electricity prices and volatility are significantly increased, which result in slightly increased energy conservation and much higher energy costs of all buildings with or without DR behaviors.

[6] Reduction is calculated by comparing each of the results against the baseline case (no DR under perfect competition). A negative value indicates an increase.

7.8.6 Large-Scale DR: All Building Types

In this test case, we simulate a more diverse market in which all commercial buildings follow their own strategies to perform load reduction at peak hours. Similar to the previous case, all these commercial building agents are located in Zone 4, and each agent has unique DR threshold curves, similar to those shown in Figure 74.

This simulation is performed for the tested region over a typical meteorological summer, and we use one week in August to compare the different scenarios. Figure 77 shows the hourly load of the entire commercial building stock in Zone 4 under the condition of perfect market competition, both with and without DR. Similar to the office test case in Figure 76, DR occurs when the electricity price rises above the pre-determined thresholds. But in contrast to the office case, Figure 77 indicates a larger portion of load reduction because more buildings are involved in DR actions.

In addition, the resulting electricity prices under different market competition levels are plotted in Figure 78. When compared to the previous case in Figure 75, two observations can be made. First of all, under both market competition scenarios, when all of the types of buildings perform DR, the electricity prices are much lower than they are in the same market competition scenarios without demand response. This result occurs because the equilibrium prices become lower when a large number of buildings reduce the demand at peak hours while the supply remains the same. Secondly, electricity prices in scenarios with DR reduce more when large-scale participation is deployed, in comparison with the prices reduction of the scenarios without DR. The main reason for this result is that in this case, the demand side is more sensitive in reacting to the price, which prevents the electricity price from rising higher.

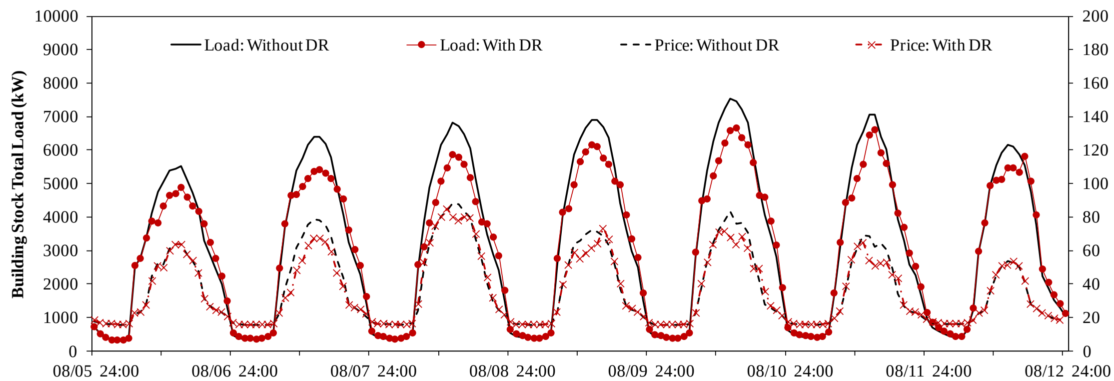


Figure 77 Building stock total load with and without DR under perfect market competition during August 5–11

Statistics of this test case are shown in Table 32. Compared to results of the previous test case, when more buildings deploy DR, electricity prices become less volatile (as reflected in the standard deviation value for price). In terms of electricity consumption, participation in DR by a larger-scale representation of buildings results in lower total electricity consumption of the building stock. This indicates a lower total cost under both market structures, compared to the previous test case.

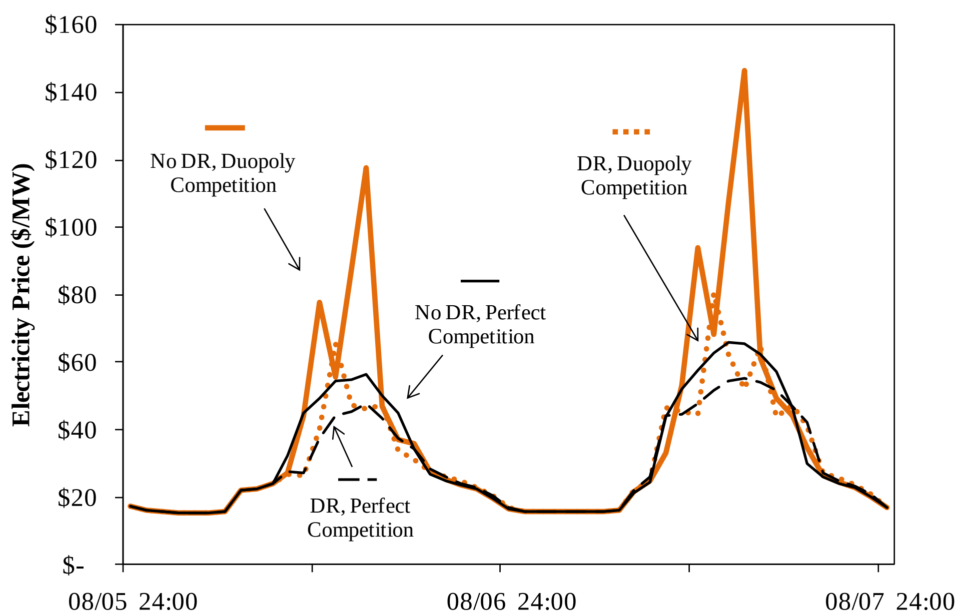


Figure 78 Electricity price under different market competition levels with all buildings performing DR during August 5–6

Table 32 Comparison of electricity price, consumption and cost under different market structures (Large Scale DR)

Outputs under Four Scenario	StdDev	Sum	Reduction[7]
Price ($/MWh)			
(1) No DR, Duopoly	39.5	N/A	-101.6%
(2) No DR, Perfect	19.6	N/A	0
(3) DR, Duopoly	20.6	N/A	-5.2%
(4) DR, Perfect	17.7	N/A	9.6%
Consumption (MWh)			
(1) No DR, Duopoly	N/A	2,205	0
(2) No DR, Perfect	N/A	2,205	0
(3) DR, Duopoly	N/A	2,120	3.9%
(4) DR, Perfect	N/A	2,130	3.4%
Cost ($M)			
(1) No DR, Duopoly	N/A	139.1	-36.0%
(2) No DR, Perfect	N/A	102.3	0
(3) DR, Duopoly	N/A	98.5	3.7%
(4) DR, Perfect	N/A	93.2	8.9%

7.9 Concluding Remarks

This chapter presents an agent-based simulation platform to model the diverse and dynamic impacts when demand response is practiced by commercial buildings and to explore their impacts on the electricity prices at different market competition levels. Three test cases demonstrate the capability of the proposed platform to estimate both energy and monetary consequences of DR for commercial buildings participating in the

[7] Reduction is calculated by comparing each of the results against the baseline case (no DR under perfect competition). A negative value indicates an increase

electricity market. By comparing two different scales of demand response participation at two market competition levels, we draw the following conclusions:

1) Demand response actions by commercial buildings shave the load profile at the peak hours and reduce the volatility of electricity demand. This phenomenon is more significant under duopoly market competition because of its higher electricity prices. This finding is also true when there is a larger-scale representation of buildings participating in DR.
2) Demand response actions by commercial buildings reduce electricity prices and volatility when there are more buildings deploying DR. This conclusion applies to both the perfect and the duopoly competition markets. Electricity prices under duopoly market competition are higher and more volatile than are the prices under perfect market competition. However, this difference is reduced when more buildings deploy DR.
3) Demand response actions by commercial buildings reduce building electricity cost. However, under market competition, larger-scale participation in DR results in reduced monetary savings for buildings.

Lastly from the modeling and simulation perspective, the test cases of this chapter have proven the hypothesis that the method of using a prototype-based building stock model with ABMS provides unique capabilities and comprehensive functions to analyzing the interaction between commercial buildings and the power grid.

8 CLOSURE

8.1 Summary

The general problem addressed in this thesis is how to assess the combined impact of energy-related interventions in the built environment beyond the single building level. Within this field, this research strives to more thoroughly examine how buildings perform aggregately in energy usage by focusing on how to tackle three major technical challenges: (1) quantifying building energy performance in an objective and scalable manner, (2) mapping building stock model space to real-world data space, and (3) quantifying and evaluating energy intervention behaviors of a building stock. This thesis presents three methodologies accordingly. To address the first challenge, this thesis develops a normative building energy model that can rapidly estimate single building energy performance with respect to its design and operational characteristics. To address the second challenge, the thesis proposes a statistical procedure using regression and Markov chain Monte Carlo (MCMC) sampling techniques to inversely estimate building parameters based on building stock energy consumption survey data. The outcomes of this statistical procedure validate the approach of using prototypical buildings for two types of intervention analysis: energy retrofit and demand response. These two cases are implemented in an agent-based modeling and simulation (ABMS) framework to tackle the third challenge.

This research hypothesizes that a new paradigm of aggregation of large-scale building stocks can lead to (1) an accurate and efficient intervention analysis model and

(2) a functionally comprehensive decision support tool for building stock energy intervention analysis. To test the first major hypothesis, this thesis develops five measurable sub-hypotheses and creates a set of mathematical experiments to test them. To test the second major hypothesis, this thesis implements two simulation platforms for large-scale retrofit modeling for energy policy analysis, and price-based demand response analysis. The proposed model has been demonstrated in several test cases in this thesis and shown to be capable for the target purposes.

This research contributes to the body of knowledge pertaining to building energy modeling beyond the single building scale. The proposed framework can be used by energy policy makers and utilities to evaluate energy retrofit incentives and demand-response program economics.

8.2 Findings and Conclusions

Based on the above-mentioned hypothesis testing and computational experiments, this research has five major findings and conclusions.

8.2.1 From the Single Building Modeling Perspective

This thesis has successfully proved that a well-established normative building energy model yields to similar total energy consumption results, compared to those calculated by dynamic simulation models such as Energy Plus. However, this finding strongly relies on the fact that both models are using exactly the same inputs. Given the simplicity and the scalability of the normative model, this finding implies that one can use the normative model for large-scale building stock energy modeling instead of dynamic models.

8.2.2 From the Building Stock Description Perspective

This thesis proposes a method to replicate individual buildings in a building stock, based on estimated design and operational parameter distributions of those buildings. The estimation process, based on linear regression analysis and MCMC inverse sampling techniques, has shown plausible agreement with measured energy survey data. This statistical approach can be used to populate a large number of buildings with limited data, and update their estimations efficiently when new data become available. However, this replication process is limited to one formula per city, and is not robust enough in the sampling process.

8.2.3 From the Building Stock Modeling Perspective

To more efficiently model building-stock interventions, this research proposes a prototype-based building stock modeling framework. This framework is proven to be adequate to predict the impact of energy-related interventions in the building stock, compared to the statistical approach mentioned above, and the massive approach that models thousands of individual buildings. This finding cannot be applied to predicting the *absolute* energy consumption of a building stock at any time. Instead, the framework is capable of predicting the *relative* increase or decrease of building-stock energy consumption compared to its baseline.

8.2.4 From the Energy Efficiency Policy Analysis Perspective

This thesis joins the prototype-based, building-stock model with the agent-based modeling and simulation (ABMS), and developed a tool for large-scale retrofit analysis. Simulation results suggest that policy-initiated changes to baseline decision thresholds yield observable impacts to the building stock energy consumption. Simulation results support the idea that promoting energy-efficiency technologies, even in a random way, have the potential to yield improvement in energy efficiency. However, the level of such improvement is not as high as expected. Taking the Better Buildings Initiative as an example, in the test case, 20% energy savings of commercial buildings in the State of Illinois is hard to achieve, unless building owners are provided with adequate incentives.

The work and tests described in this chapter implies that achieving commercial building energy efficiency targets most likely depends on the dynamics between the various market participants and the way those dynamics are impacted by different physical and institutional constraints. Studying infrastructure, policy, and behavioral factors relevant to meeting sector-wide energy efficiency targets by developing an agent-based model of the commercial buildings sector generates promising results. In this sense, we are interested in gaining confidence in both the structure of the model and in its simulation output.

8.2.5 From the Demand-Response Analysis Perspective

This thesis has joined the prototype-based building stock model with the agent-based modeling and simulation (ABMS), and developed a methodology for demand response (DR) modeling at the level of load service entities. Three test cases demonstrate the capability of the proposed method in estimating both energy and monetary consequences of DR for commercial buildings participating in the electricity market.

The simulation results indicate that (1) DR actions by commercial buildings shave the load profile at the peak hours and reduce the volatility of electricity demand. This phenomenon is more significant under duopoly market competition because of its higher electricity prices. This finding is also true when there is a larger-scale representation of buildings participating in DR. (2) DR actions by commercial buildings reduce electricity prices and volatility when there are more buildings deploying DR. This conclusion applies to both the perfect and the duopoly competition markets. Electricity prices under duopoly market competition are higher and more volatile than are the prices under perfect market competition. However, this difference is reduced when more buildings deploy DR. (3) DR actions by commercial buildings reduce building electricity cost. However, under market competition, larger-scale participation in DR results in reduced monetary savings for buildings.

8.3 Future Work

This thesis has revealed interesting research questions and limitations that can lead to future research topics.

8.3.1 On the Prototype-based Building-Stock Model

The DOE reference buildings were developed based on the ASHRAE 90.1 standard. They are never calibrated by actual energy consumption data, for instance, CBECS data sets. Future work on the development of reference buildings can use Bayesian calibration techniques to create more statistically representative models.

8.3.2 On the Inverse Problem Solving Technique

In Section 3.4, we used an inverse problem sampling technique to estimate the posterior distributions of building design and operational parameters in the building stock. In this process, we have neglected errors between the data space and the model space. These errors may include measurement errors, modeling errors, methodological errors, etc. We hypothesize that if we are only interested in comparative analysis where the result is based on the difference between two model interventions, the error terms can be cancelled out. However, this hypothesis cannot be fully tested without developing a method that could quantify these errors. A better statistical technique could be determined to fully estimate the above mentioned errors in the inverse problem-solving process to achieve better predictions.

Another possible application of this inverse problem technique is on the campus or district scale. Using aggregated energy meter data of the area, specifications of individual buildings could be estimated for campus-level retrofit decision support. At this scale, measurement data can be more easily obtained to calibrate the prediction and validate this methodology.

8.3.3 On the Energy Policy Analysis

This thesis presents a deterministic model. However, in reality many input parameters are not specific values. The next step of applying this model for energy policy analysis would be to embrace the stochastic paradigm by using statistical sampling techniques like Monte Carlo.

Another possible application of the proposed model is a national or census-zone scale analysis. This application would target macro impacts using bottom-up models. It could then be compared with the results from NEMS.

8.3.4 On the Owner Retrofit Decision Analysis

In this thesis, building owners do not influence one another's decisions. It would be interesting to explore how individual building owners, ESCO companies, and technology providers can interact. The amount of capital available in the market should also be considered to verify if an energy-efficiency target is achievable. Agent-based modeling and simulation is the best tool to tackle this research topic.

The decision making perspective also deserves further study. When building owners are triggered to evaluate retrofit alternatives, how actually behave in reality is still unknown. Besides, a more comprehensive database of retrofit technologies that indicates physical and economical specifications is still in its infancy. Relevant industry surveys and interviews of real owners could contribute to unpack the paradigm of the retrofit decision making process.

8.3.5 On the Large-Scale Demand Response Analysis

The demand response model proposed in this thesis can be connected to two existing research directions. First, it can be connected with the current power grid dispatch model to evaluate the effectiveness of filling the valley of demand profiles. Second, it can be connected with the distribution network models to explore micro-level grid stability and energy efficiency issues.

In addition, a sensitivity analysis of environmental impacts (such as reduction in CO_2 emission) of demand response can also be simulated using the proposed building stock model.

APPENDIX: MODELED RETROFIT TECHNOLOGIES

In the retrofit analysis application, we have developed a set of typical retrofit technologies for commercial buildings in the U.S. In these tables, the retrofit technologies are organized under three hierarchical levels:

- Category: Building functional systems
- Energy efficiency measure (EEM): Generic approaches to improve building energy performance
- Retrofit Technology: Specific technologies available in the market

In the following tables, building parameter values are denoted as follows: $X^{(t)}$ is the value at year *t*, $X^{(t+1)}$ is the value at year (t+1), $X^{(0)}$ is the initial value at the beginning of simulation, and $X^{(retro)}$ is the initial value after the previous retrofit.

Physical and cost values of the retrofit technologies are found from various sources, including EIA (2009), UW Milwukee (2012), US EPA (2012), Green Options (2012), Navigant Consulting (2007), Crawley (2008), Augenbroe et al. (2010), Wulfinghoff (2000), ISO (2008), and Mewis (2010). We have not yet found reliable references for the underlined values.

1. Envelope

EEM	Retrofit Technology RT_j	Affected Parameters $\boldsymbol{X}_j$ (Unit)	Retrofit Fn. f_j $\boldsymbol{X}_j^{(t+1)} = f_j[\boldsymbol{X}_j^{(t)}]$	Invest. ($/m^2 Ref. Area)	Ref. Area
Roof renovation	R5 insulation: extruded polystyrene, 25 PSI[8], 1"	Roof U-factor [W/(m^{2}K)]	$\frac{1}{1/X^{(t)}+1/1.14}$	10.66	Roof
	R20 insulation: extruded polystyrene, 25 PSI, 4"	Roof U-factor [W/(m^{2}K)]	$\frac{1}{1/X^{(t)}+1/0.28}$	35.63	Roof
	Green roof, R4	Roof U-factor [W/(m^{2}K)]	$\frac{1}{1/X^{(t)}+1/1.42}$	216.00	Roof
		Roof absorption coefficient	0.225		
		Roof emissivity	0.9		
	Cool roof, polished aluminum foil	roof absorption coefficient	0.15	12.15	Roof
		Roof emissivity	0.85		
Wall insulation	R5 insulation: extruded polystyrene, 25 PSI, 1"	Opaque Wall U-factor [W/(m^{2}K)]	$\frac{1}{1/X^{(t)}+1/1.14}$	12.16	Wall
	R15 insulation: extruded polystyrene, 25 PSI, 3"	Opaque Wall U-factor [W/(m2K)]	$\frac{1}{1/X^{(t)}+1/0.38}$	23.03	Wall
Window upgrade	Double glazing clear U2.95 SC0.88	Window U-factor [W/(m^{2}K)]	2.95	12.16	Window
		Window Solar Transmittance	0.88		
	Double glazing low-e U2.90 SC0.55	Window U-factor [W/(m^{2}K)]	2.9	30.45	Window
		Window Solar Transmittance	0.55		
	Triple glazing low-e 12mm argon	Window U-factor [W/(m^{2}K)]	0.8	85.00	Window
		Window Solar Transmittance	0.23		
Enhanced shading	Overhangs, fins, or blinds	Window Shading Coefficient	0.7	100.00	Window
Inf. reduction	Infiltration reduction	Infiltration Rate (ACH[9])	0.9*$X^{(t)}$	5.00	Floor

[8] PSI: Pounds per square inch

[9] ACH: Air change per hour

2. HVAC

EEM	Retrofit Technology RT_j	Affected Parameters $\boldsymbol{X}_j$ (Unit)	Retrofit Fn. f_j $\boldsymbol{X}_j^{(t+1)} = f_j[\boldsymbol{X}_j^{(t)}]$	Invest. ($/m^2 Ref. Area)	Ref. Area
Cooling and heating system retrofit	Re-commissioning	Cooling COP (kW/kW)	$0.9{*}X^{(retro)}$	1.08	Floor
		Heating system efficiency	$0.9{*}X^{(retro)}$		
	High-efficiency centrifugal chiller	Cooling COP (kW/kW)	7.3	14.05	Floor
	High-efficiency natural gas boiler	Heating Efficiency (kW/kW)	0.96	89.51	Floor
		Heating Energy Carrier (1: Electricity; 2: Natural gas)	2		
	Electric rooftop heat pump	Heating Efficiency (kW/kW)	3.4	216.54	Floor
		Heating Energy Carrier (1: Electricity; 2: Natural gas)	1		
		Cooling COP (kW/kW)	3.5		
	Ground source heat pump	Heating Efficiency (kW/kW)	4.9	380.80	Floor
		Heating Energy Carrier (1: Electricity; 2: Natural gas)	1		
		Cooling COP (kW/kW)	8.1		
Energy recovery	Air-to-air heat wheel	Heat Recovery Efficiency	0.7	5.00	Floor
Pump system upgrade	VSD[10] pump system	Pump Control Factor (3: No auto-control; 2: More than 50% auto-control)	2	5.00	Floor

[10] VSD: Variable-speed drive

3. Lighting

EEM	Retrofit Technology RT_j	Affected Parameters $\boldsymbol{X}_j$ (Unit)	Retrofit Fn. f_j $\boldsymbol{X}_j^{(t+1)} = f_j[\boldsymbol{X}_j^{(t)}]$	Invest. ($/m^2 Ref. Area)	Ref. Area
Lighting fixture replacement	2-lamp T-8 lighting fixture	Lighting Power Intensity (W/m^2)	8.6	8.82	Floor
	Light-emitting diode (LED)	Lighting Power Intensity (W/m^2)	6.88	10.39	Floor
Day-lighting control	Day-lighting sensor system	Daylight Sensor Factor (1: No sensor; 2: With sensor)	2	8.82	Floor
Lighting sensor	Occupancy sensor system	Occupancy Sensor Factor (1: No sensor; 2: With sensor)	2	8.82	Floor

4. Domestic Hot Water (DHW)

EEM	Retrofit Technology RT_j	Affected Parameters $\boldsymbol{X}_j$ (Unit)	Retrofit Fn. f_j $\boldsymbol{X}_j^{(t+1)} = f_j[\boldsymbol{X}_j^{(t)}]$	Invest. ($/m^2 Ref. Area)	Ref. Area
Heater replacement	Improved condensing gas water heater	DHW Efficiency	0.94	1.50	Floor
		DHW Energy Carrier (1: Electricity, 2: Natural gas)	2		

5. Appliances

EEM	Retrofit Technology RT_j	Affected Parameters $\boldsymbol{X}_j$ (Unit)	Retrofit Fn. f_j $\boldsymbol{X}_j^{(t+1)} = f_j[\boldsymbol{X}_j^{(t)}]$	Invest. ($/m^2 Ref. Area)	Ref. Area
High-efficiency appliances	EnergyStar equipment	Equipment power intensity (W/m^2)	$0.7 * X^{(0)}$	2.40	Floor

REFERENCES

Anderson, B., Chapman, P., Cutland, N., Dickson, C., Doran, S., Henderson, G., . . . Shorrock, L. (2001). BREDEM-8: Model Description 2001 Update. Watford, UK: Building Research Establishment.

Augenbroe, G., Lee, S., Lee, J.-k., & Zhao, F. (2010). EPSCT: Energy Performance Standard Calculation Toolkit, Retrieved 2011, from http://www.epsct.org

Axtell, R. L., Epstein, J. M., Dean, J. S., Gumerman, G. J., Swedlund, A. C., Harburger, J., . . . Parker, M. (2002). *Population growth and collapse in a multiagent model of the Kayenta Anasazi in Long House Valley*. Paper presented at the National Academy of Sciences of the USA.

Bandura, A. (2001). Social Cognitive Theory: An Agentic perspective. *Annual Review of Psychology, 52*, 1-26.

Billinton, R., & Li, W. (1994). *Reliability assessment of electric power systems using Monte Carlo methods*. New York, USA: Plenum Press.

Boardman, B. (2007). Examining the carbon agenda via the 40% house scenario. *Building Research & Information, 35*(4), 363-378.

Brown, M. A., Kreitler, V., & Wolfe, A. K. (1996). The Persistence of Program Impacts: Methods, Applications, and Selected Findings. *Energy Services Journal, 2*(3), 167-192.

BSi. (2007a). BS EN 15242 *Ventilation for buildings—Calculation methods for the determination of air flow rates in buildings including infiltration*: Britsh Standard.

BSi. (2007b). BS EN 15316-3-2 Heating systems in buildings—Method for calculation of system energy requirements and system efficiencies *Part 3-2: Domestic hot water systems, distribution*. London, UK: Britsh Standard.

Bushnell, J. B., & Saravia, C. (2002). An Empirical Assessment of the Competitiveness of the New England Electricity Market (Vol. CSEM Working Paper 101).

Callaway, D. (Nov 3, 2009). Aggregated Electricity Load Modeling and Control for Regulation and Load Following Ancillary Services, from http://www.pserc.wisc.edu/documents/general_information/presentations/pserc_seminars/5psercsemin/callaway_load_aggregation_pserc_nov09.pdf

Cederman, L. (2003). Modeling the Size of Wars: From Billiard Balls to Sandpiles. *American Political Science Review, 97*(1).

CEN/TC 169. (2006). prEN 15193: Energy Performance of Buildings — Energy Requirements for Lighting *Annex E*.

Chassin, D. P., Schneider, K., & Gerkensmeyer, C. (2008). *GridLAB-D: An open-source power systems modeling and simulation environment.* Paper presented at the Proceedings of IEEE PES Transmission and Distribution Conference and Exposition, Chicago, IL, USA.

Chung, W. (2011). Review of building energy-use performance benchmarking methodologies. *Applied Energy, 88*(5), 1470-1479. doi: 10.1016/j.apenergy.2010.11.022

CIBSE. (2006). Guide A: Environmental Design. London, UK: Chartered Institution of Buildings Services Engineers.

Clarke, J. A., Johnstone, C. M., Kondratenko, I., Lever, M., McElroy, L. B., Prazeres, L., . . . Peart, G. (2004). Using simulation to formulate domestic sector upgrading strategies for Scotland. *Energy and Buildings*, *36*(8), 759-770.

Colley, B., Borgeson, S., Selkowitz, S., Apte, J., Mathew, P., & Haves, P. (2009). Towards a very low-energy building stock: modelling the US commercial building sector to support policy and innovation planning. *Building Research & Information*, *37*(5-6), 610-624. doi: 10.1080/09613210903189467

Conzelmann, G., Boyd, G., Koritarov, V., & Veselka, T. (2005). *Multi-agent power market simulation using EMCAS.* Paper presented at the Proceedings of IEEE Power Engineering Society General Meeting.

Crawley, D. (2008). *Building Performance Simulation: A Tool for Policymaking*. Ph.D. Dissertation, University of Strathclyde, Glasgow, UK.

Dam, K. H. v., Houwing, M., & Bouwmans, I. (2008). Agent-based control of distributed electricity generation with micro combined heat and power-cross-sectoral learning for process and infrastructure engineers. *Computers & Chemical Engineering*, *32*(1-2), 205-217.

De Wilde, P., & Tian, W. (2010). Predicting the performance of an office under climate change: A study of metrics, sensitivity and zonal resolution. *Energy and Buildings, 42*(10), 1674-1684.

de Wit, M. S. (2001). *Uncertainty in predictions of thermal comfort in buildings.* PhD Thesis PhD Thesis, Technische Universiteit Delft, Netherlands.

Deru, M., Field, K., Studer, D., Benne, K., Griffith, B., Torcellini, P., . . . Crawley, D. (2011). U.S. Department of Energy Commercial Reference Building Models of the National Building Stock. Golden, CO: National Renewable Energy Laboratory.

DOE. (2009). Commercial Reference Buildings, Retrived March 12, 2012, from http://www1.eere.energy.gov/buildings/commercial_initiative/reference_buildings.html

DOE. (2010). EnergyPlus 5.0. Retrieved July 27, 2010, from http://apps1.eere.energy.gov/buildings/energyplus/

Dunn, G., & Knight, I. (2005). Small power equipment loads in UK office environments. *Energy and Buildings, 38*, 87-91.

EIA. (2006). 2003 Commercial Buildings Energy Consumption Survey (CBECS), from http://www.eia.doe.gov/emeu/cbecs/contents.html

EIA. (2009). The National Energy Modeling System: An Overview 2009. Washington, DC: U.S. Energy Information Administration.

EIA. (2011). Annual Energy Outlook 2011.

Emonet, T., Macal, C. M., North, M. J., Wichersham, C. E., & Cluzel, P. (2005). AgentCell: a digital single-cell assay for bacterial chemotaxis. *Bioinformatics, 21*(11), 2714-2721.

Enkvist, P.-A., Nauclér, T., & Rosander, J. (2007, February 2007). A cost curve for greenhouse gas reduction. *The McKinsey Quarterly, 5*.

EPA. (2007). ENERGY STAR® Performance Ratings Technical Methodology for Office, Bank/Financial Institution, and Courthouse.

Erev, I., & Roth, A. (1998). Predicting How People Play Games: Reinforcement Learning in Experimental Games with Unique, Mixed Strategy Equilibria. *The American Economic Review, 88*(4), 848-881.

Exarchakos, L., Leach, M., & Exarchakos, G. (2009). Modelling electricity storage systems management under the influence of demand-side management programs. *International Journal of Energy Research, 33*(1), 62-76.

Fabra, N., & Toro, J. (2005). Price wars and collusion in the Spanish electricity market. *International Journal of Industrial Organization, 23*(3-4), 155-181.

Farahbakhsh, H., Ugursal, V. I., & Fung, A. S. (1998). A residential end-use energy consumption model for Canada. *International Journal of Energy Research, 22*(13), 1133-1143.

Federal Energy Regulatory Commission. (2008). A national assessment of demand response potential. Washington, D.C.

FERC. (2006). United States of America Electricity Energy Market Competition Task Force and the Federal Energy Regulatory Commission: Federal Energy Regulatory Commission.

Firth, S. K., Lomas, K. J., & Wright, A. J. (2010). Targetting household energy-efficiency measures using sensitivity analysis. *Building Research & Information, 38*(1), 25-41.

Geyer, C. (2003a, Feb. 15). Burn-In is Unnecessary Retrieved March 10, 2012, from http://users.stat.umn.edu/~geyer/mcmc/burn.html

Geyer, C. (2003b, Feb. 15). One Long Run in MCMC Retrieved March 10, 2012, from http://users.stat.umn.edu/~geyer/mcmc/one.html

Gotts, N. M., Polhill, J. G., & Law, A. N. R. (2003). Agent-Based Simulation in the Study of Social Dilemmas. *Artificial Intelligence Review, 19*, 3-92.

Granade, H. C., Creyts, J., Derkach, A., Farese, P., Nyquist, S., & Ostrowski, K. (2009). Unlocking Energy Efficiency in the U.S. Economy *McKinsey Global Energy and Materials*: McKinsey & Company.

Green Options. (2012). Lifetime Costs Of Light Bulbs Retrieved March 26, 2012, from http://www.greenoptions.com/a/lifetime-costs-of-light-bulbs

Griffith, B., Long, N., Torcellini, P., Judkoff, R., Crawley, D., & Ryan, J. (2007). Assessment of the Technical Potential for Achieving Net Zero-Energy Buildings in the Commercial Sector. Golden, Colorado: National Renewable Energy Laboratory.

Griffith, B., Long, N., Torcellini, P., Judkoff, R., Crawley, D., & Ryan, J. (2008). Methodology for Modeling Building Energy Performance across the Commercial Sector: National Renewable Energy Laboratory, U.S. Department of Energy.

Guerci, E., & Rastegar, M. A. (2009). From Uniform Auction to Discriminatory Auction: Assessment of the Restructuring Proposal for the Italian Electricity Day-Ahead Market *working paper*: EUI RSCAS.

Gurney, K., Mendoza, D., Geethakumar, S., Zhou, Y., Chandrasekaran, V., Miller, C., . . . Can, S. d. l. R. d. (2008). Vulcan Science Methods Documentation, Version 2.0: Purdue University.

Hanson, D., & Laitner, J. A. S. (2004). An integrated analysis of policies that increase investments in advanced energy-efficient/low-carbon technologies. *Energy Economics, 26*(4), 739-755. doi: 10.1016/j.eneco.2004.04.020

Healy, W. M., Lutz, J. D., & Lekov, A. B. (2003). Variability in energy factor test results for residential electric water heaters. *HVAC&R Research, 9*(4), 435-449.

Henderson, G., & Shorrock, L. D. (1986). BREDEM—The BRE domestic energy model: Testing the predictions of a two-zone version. *building Services Engineering Research & Technology, 7*(2), 87-91.

Hendron, R. (2008). Building America Research Benchmark Definition. Golden, CO: National Renewable Energy Laboratory.

Hens, H., Verbeeck, G., & Verdonck, B. (2001). Impact of energy efficiency measures on the CO2 emissions in the residential sector, a large scale analysis. *Energy and Buildings, 33*, 275-281.

Heo, Y. (2011). *Bayesian calibration of building energy models for energy retrofit decision-making under uncertainty.* Ph.D. Dissertation, Georgia Institute of Technology, Atlanta, GA, USA.

Hogeling, J., & Van Dijk, D. (2008). P60 More Information on the Set of CEN Standards for the EPBD. Retrieved from http://www.buildup.eu/publications/1484

Hu, H. (2009). *Risk-Conscious Design of Off-Grid Solar Energy Houses.* Ph.D. Dissertation, Georgia Institute of Technology, Atlanta, GA.

Huang, J., Akbari, H., Rainer, L., & Ritshard, R. (1991). 481 Prototypical Commercial Buildings for 20 Urban Market Areas. Berkeley, CA: Lawrence Berkeley National Laboratory.

Huang, J., & Franconi, E. (1999). Commercial Heating and Cooling Loads Component Analysis. Berkeley, CA: Lawrence Berkeley National Laboratory.

Huang, J., Roberson, J. A., & Sezgen, O. (2005). Analysis of 1999 CBECS Data by Commercial Building Type. Berkeley, CA: Lawrence Berkeley National Laboratory.

IEA. (2008). World Energy Outlook. Paris, France: International Energy Agency (IEA).

IPCC. (2007). Summary for Policymakers. In B. Metz, O. R. Davidson, P. R. Bosch, R. Dave & L. A. Meyer (Eds.), *Climate Change 2007: Mitigation. Contribution of Working Group III to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change*. United Kingdom and New York, NY, USA.: Cambridge University Press.

ISO. (2008). 13790:2008 *Energy Performance of Buildings—Calculation of Energy Use for Space Heating and Cooling*.

Jarnagin, R. E., & Bandyopadhyay, G. K. (2010). Weighting Factors for the Commercial Building Prototypes Used in the Development of ANSI/ASHRAE/IENSA Standard 90.1-2010. Richland, Washington: Pacific Northwest National Laboratory.

Jiang, B., & Yao, X. (2010). Chapter 1: Geospatial Analysis and Modeling of Urban Structure and Dynamics: An Overview. In B. Jiang & X. Yao (Eds.), *Geospatial Analysis and Modeling of Urban Structure and Dynamics* (pp. 3-11): Springer.

Johnson, D., Lowe, R., & Bell, M. (2005). An exploration of the technical feasibility of achieving CO2 emission rductions in excess of 60% within the UK housing stock by the year 2050? *Energy Policy, 33*(13), 1643-1659.

Jones, P. J., Lannon, S., & Williams, J. (2001). *Modelling building energy use at urban scale.* Paper presented at the the 7th International IBPSA Conference, Rio de Janeiro, Brazil.

Judkoff, R. (1988). Validation of Building Energy Analysis Simulation Programs at the Solar Energy Research Institute. *Energy and Buildings, 10*(3), 235.

Judkoff, R., Wortman, D., & Burch, J. (1983). Measured versus Predicted Performance of the SERI Test House: A Validation Study. Golden, CO: Solar Energy Research Institute (now National Renewable Energy Laboratory).

K, S., K, V. d. M., & D, v. O. (2009). limSolve: Solving Linear Inverse Models. Version 1.5.2, from http://cran.r-project.org/web/packages/limSolve/

Kanaga, E. G. M., & Valarmathi, M. L. (2012). Multi-agent based Patient Scheduling Using Particle Swarm Optimization. *Procedia Engineering, 30*(0), 386-393. doi: 10.1016/j.proeng.2012.01.876

Kavgic, M., Mavrogianni, A., Mumovic, D., Summerfield, A., Stevanovic, Z., & Djurovic-Petrovic, M. (2010). A Review of Bottom-up Building Stock Models for Energy Consumption in the Residential Sector. *Building and Environment, 45*(7), 1683-1697. doi: DOI: 10.1016/j.buildenv.2010.01.021

Kohler, T. A., Gumerman, G.J., and Reynolds, R.G. (2005). Simulating Ancient Societies. *Scientific American, 293*(1), 76-83.

Kohn, A. E., & Katz, P. (2002). *Building Type Basics for Office Buildings*. New York, NY: John Wiley & Sons.

Lagorse, J., Paire, D., & Miraoui, A. (2010). A multi-agent system for energy management of distributed power sources. *Renewable Energy, 35*(1), 174-182. doi: 10.1016/j.renene.2009.02.029

Leach, M., Lobato, C., Hirsch, A., Pless, S., & Torcellini, P. (2010). Technical Support Document: Strategies for 50% Energy Savings in Large Office Buildings: National Renewable Energy Laboratory.

Lee, S. H. (2011). *Management of building energy consumption and energy supply network on campus scale.* Ph.D. dissertation, Georgia Institute of Technolgoy.

Lee, S. H., Zhao, F., & Augenbroe, G. (2011, November 14-16). *The use of normative calculation beyond building performance rating systems.* Paper presented at the Building Simulation 2011, Sydney, Australia.

Li, H., & Tesfatsion, L. (2009). Development of Open Source Software for Power Market Research: The AMES Test Bed. *Journal of Energy Markets, 2*(2), 111-128.

Loutzenhiser, P. G., Manz, H., Moosberger, S., & Maxwell, G. M. (2009). An empirical validation of window solar gain models and the associated interactions. *International Journal of Thermal Sciences, 48*, 85-95.

Luke, S., Balan, G. C., Sullivan, K., & Panait, L. (2003). MASON: A new multi-agent simulation toolkit Retrieved March 26, 2012, from http://cs.gmu.edu/~eclab/projects/mason/

Macal, C. M., & North, M. J. (2005). *Tutorial on Agent-based Modeling and Simulation.* Paper presented at the 2005 Winter Simulation Conference.

Macdonald, I. A. (2002). *Quantifying the effects of uncertainty in building simulation.* Ph.D. Dissertation, University of Strathclyde.

Macy, M. W., & Willer, R. (2002). From Factors to Actors: Computational Sociology and Agent-Based Modeling. *Annual Review of Sociology*.

Manley, M., & Kim, Y. S. (2012). Modeling emergency evacuation of individuals with disabilities (exitus): An agent-based public decision support system. *Expert Systems with Applications, 39*(9), 8300-8311. doi: 10.1016/j.eswa.2012.01.169

Mansur, E. T. (2003). Vertical Integration in Restructured Electricity Markets: Measuring Market Efficiency and Firm Conduct (Vol. CSEM Working Paper PWP-117).

Martinez-Moyano, I. J., Mahalik, M. R., Graziano, D. J., & Conzelmann, G. (2010). Developing an Agent-based Model of the U.S. Commercial Buildings Sector: Literature Review (D. a. I. Science, Trans.). Argonne, IL: Argonne National Laboratory.

Martinez-Moyano, I. J., Simunich, K. L., Bragen, M., Zhou, Z., Zhao, F., & Augenbroe, G. (2011). *Modeling the Commercial Building Stock*. Internal Presentation. Argonne National Laboratory. Chicago, United States.

Martinez-Moyano, I. J., Zhao, F., Simunich, K. L., Graziano, D. J., & Conzelmann, G. (2011, June 25-29, 2011). *Modeling the Commercial Buildings Sector: An Agent-based Approach.* Paper presented at the 2011 ASHRAE Annual Conference, Montreal, Canada.

McArthur, S. (2011). IEEE Power & Energy Society Multi-Agent Systems Working Group Retrieved April 19th, 2011, from http://ewh.ieee.org/mu/pes-mas

McGraw Hill. (2011). Dodge Database Retrieved May 1, 2011, from http://dodge.construction.com/

McKay, M. D., Beckman, R. J., & Conover, W. J. (1979). A Comparison of Three Methods for Selecting Values of Input Variables in the Analysis of Output from a Computer Code. *Technometrics, 21*(2), 239-245.

Meersche, K. V. d., Soetaert, K., & Oevelen, D. V. (2009). xsample(): an R Function for Sampling Linear Inverse Problems. *Journal of Statistical Software, Code Snippets, 30*(1), 1-15.

Meinel, G., Hecht, R., & Herold, H. (2009). Analyzing Building Stock Using Topographic Maps and GIS. *Building Research & Information, 37*(5/6), 468-482. doi: 10.1080/09613210903159833

Mewis, B. (2010). *RSMeans Commercial Renovation Cost Data 2011* (32 Annual edition ed.): R.S. Means Company.

Millet, J.-R. (2007). *The simple hourly method of prEN 13790: a dynamic method for the future.* Paper presented at the Chima 2007 WellBeing Indoors, Helsinki, Finland.

Minar, N., Burkhart, R., Langton, C., & Askenazi, M. (1996). The Swarm Simulation System: A Toolkit for Building Multi-Agent Systems. Santa Fe, NM: Santa Fe Institute.

MIT Media Laboratory. (2000). StarLogo Retrieved March 26, 2012, from http://education.mit.edu/starlogo/

Monts, J. K., & Blissett, M. (1982). Assessing Energy Efficiency And Energy Conservation Potential Among Commercial Buildings: A Statistical Approach. *Energy, 7*(10), 861-869.

Morris, M. D. (1991). Factorial Sampling Plans for Preliminary Computational Experiments. *Technometrics, 33*, 161–174.

Nadel, S., Shipley, A., & Elliott, R. N. (2004). *The technical, economic and achievable potential for energy-efficiency in the U.S. – a meta-analysis of recent studies*. Paper presented at the ACEEE Summer Study on Energy Efficiency in Buildings, Pacific Grove, CA.

Natarajan, S., & Levermore, G. J. (2007). Predicting future UK housing stock and carbon emissions. *Energy Policy, 35*, 5719-5722.

Navigant Consulting. (2007). EIA—Technology Forecast Updates: Residential and Commercial Building Technologies—Reference Case (Second Edition (Revised) ed.): Navigant Consulting, Inc.

Nielsen, T. R. (2005). Simple tool to evaluate energy demand and indoor environment in the early stages of building design. *Solar Energy, 78*, 73–83.

North, M. J., Howe, T. R., Collier, N. T., & Vos, J. R. (2007). A Declarative Model Assembly Infrastructure for Verification and Validation. In S. Takahashi, D. L. Sallach & J. Rouchier (Eds.), *Advancing Social Simulation: The First World Congress*. Heidelberg, FRG: Springer.

North, M. J., & Macal, C. M. (2007a). *Managing Business Complexity: Discovering Strategic Solutions with Agent-Based Modeling and Simulation*. New York, New York: Oxford University Press.

North, M. J., & Macal, C. M. (2007b). *Managing Business Complexity: Discovering Strategic Solutions with Agent-based Modeling and Simulation*. New York, NY: Oxford University Press, Inc.

ON. (2007). EN 15243 *Ventilation for buildings — Calculation of room temperatures and of load and energy for buildings with room conditioning systems*. Vienna, Austria: ON Österreichisches Normungsinstitut, Austrian Standards Institute.

Parekh, A. (2005). *Development of archetypes of building characteristics libraries for simplified energy use evaluation of houses*. Paper presented at the Ninth International IBPSA Conference, Montreal, Canada.

Phoenix Integration Inc. (2012). Model Center, 2012, from http://www.phoenix-int.com/software/phx_modelcenter_10.php

Press, W. H., Teukolsky, S. A., Vetterling, W. T., & Flannery, B. P. (1996). *Numerical Recipes in Fortran 77: The Art of Scientific Computing*. (2nd ed.): Cambridge University Press.

R Development Core Team. (2008). *R: A language and environment for statistical computing*. Vienna, Austria: R Foundation for Statistical Computing.

Raftery, A. E., & Lewis, S. M. (1995). The Number of Iterations, Convergence Diagnostics and Generic Metropolis Algorithms *In Practical Markov Chain Monte Carlo* (pp. 115-130): Chapman and Hall.

Rahimiyan, M., & Mashhadi, H. R. (2010). An Adaptive Q-Learning Developed for Agent-Based Computational Modeling of Electricity Market. *IEEE Transactions on Systems, Man, and Cybernetics – Part C: Applications and Reviews, 40*(5), 547-556.

Reed, J. H., Johnson, K., Riggert, J., & Oh, A. D. (2004). Who Plays and Who Decides: The Structure and Operation of the Commercial Building Market. Rockville, MD, USA: Innovologie, LLC.

Roase, R. H. (1990). *The Firm, The Market, and The Law*: The University of Chicago Press.

Ruchi, C. (2012). Energy analysis of the non-domestic building stock of Greater London. *Building and Environment, 51*(0), 243-254. doi: 10.1016/j.buildenv.2011.10.006

Ryan, J. D., & Nicholls, A. (2004). *Commercial building R&D program multi-year planning: opportunities and challenges.* Paper presented at the Proceedings of the ACEEE Summer Study on Energy Efficiency in Buildings, Washington, DC.

Sansregret, S., & Millette, J. (2009, July 27-30, 2009). *Development of a functionality generating simulations of commercial and institutional buildings having representative characteristcs of a real estate stock in Quebec (Canada).* Paper presented at the Eleventh International IBPSA Conference, Glasgow, Scotland.

Saravia, C. (2003). Speculative Trading and Market Performance: The Effect of Arbitrageurs on Efficiency and Market Power in the New York Electricity Market (Vol. CSEM Working Paper 121).

Schoenwald, D. A., Barton, D. C., & Ehlen, M. A. (2004). *An agent-based simulation laboratory for economics and infrastructure interdependency.* Paper presented at the Proceedings of the 2004 American Control Conference, Boston, MA, USA.

Sensfuß, F., Ragwitz, M., Genoese, M., & Möst, D. (2007). Agent-Based Simulation of Electricity Markets: A Literature Review: Fraunhofer Institute Systems and Innovation Research.

Shorrock, L., & Dunster, J. E. (1997). The physically-based model BREHOMES and its use in deriving scenarios for the energy use and carbon dioxide emissions of the UK housing stock. *Energy Policy, 25*(12), 1027-1037.

Smith, E. R., & Conrey, F. R. (2007). Agent-Based Modeling: A New Approach for Theory Building in Social Psychology. *Personality and Social Psychology Review, 11*(87).

Smith, R. L. (1984). Efficient Monte-Carlo Procedures for Generating Points Uniformly Distributed over Bounded Regions. *Operations Research, 32*(6), 1296-1308.

Snakin, J. P. A. (2000). An engineering model for heating energy and emission assessment: the case of North Karelia, Finland. *Applied Energy, 2000*(67), 353-381.

Sonderegger, R. (1978). *Dynamic Models of House Heating Based on Equivalent Thermal Parameters.* Doctoral Dissertation, Princeton University, Princeton, New Jersey. (Report PU/CES 57)

Stocki, M., Curcija, D. C., & Bhandari, M. S. (2007). The Development of Standardized Whole Building Simulation Assumptions for Energy Analysis for a Set of Commercial Buildings. *ASHRAE Transactions, 13*(2), 422-435.

Sun, J., & Tesfatsion, L. (2007). Dynamic Testing of Wholesale Power Market Designs: An Open-Source Agent-Based Framework. *Computational Economics, 30*(3), 291-327.

Swan, L. G., & Ugursal, V. I. (2009). Modeling of End-use Energy Consumption in the Residential Sector: A Review of Modeling Techniues. *Renewable and Sustainable Energy Reviews, 13*(2009), 1819-1835.

Tanikawa, H., & Hashimoto, S. (2009). Urban Stock Over Time: Spatial Material Stock Analysis Using 4d-GIS. *Building Research & Information, 37*(5/6), 483-502. doi: 10.1080/09613210903169394

Taylor, Z. T., Gowri, K., & Katipamula, S. (2008). GridLAB-D Technical Support Document: Residential End-Use Module Version 1.0. Richland, Washington: Pacific Northwest National Laboratory.

Tesfatsion, L. (2006). Agent-Based Computational Economics: A Constructive Approach to Economic Theory *Handbook of Computational Economics* (Vol. 2, pp. 831-880).

Tesfatsion, L. (2011, February 4th, 2011). ACE Research Area:Electricity Market Research Retrieved April 19th, 2011, from http://www2.econ.iastate.edu/tesfatsi/aelect.htm

The White House Office of Media Affairs. (2011). President Obama's Plan to Win the Future by Making American Businesses More Energy Efficient through the "Better Buildings Initiative", from http://www.whitehouse.gov/the-press-office/2011/02/03/president-obama-s-plan-win-future-making-american-businesses-more-energy

Thornton, B., Wang, W., Huang, Y., Lane, M., & Liu, B. (2010). Technical Support Document: 50% Energy Savings for Small Office Buildings. Richland, Washington, USA: Pacific Northwest Naitional Laboratory.

Tian, W., & Choudhary, R. (2011). *Energy Use of Buildings at Urban Scale: A Case Study of London Buildings.* Paper presented at the Building Simulation 2011 Conference, Sydney, Australia.

Tso, G. K. F., & Yau, K. K. W. (2007). Predicting electricity energy consumption: A comparison of regression analysis, decision tree and neural networks. *Energy, 32*(9), 1761-1768. doi: 10.1016/j.energy.2006.11.010

Tweed, C. (1998). Supporting argumentation practices in urban planning and design. *Computers, Environment and Urban Systems, 22*(4), 351-363.

U.S. Department of Energy. (2006). Benefits of Demand Response in Electricity Markets and Recommendations for Achieving them: Report to the United States Congress.

U.S. EIA. (2009a). Annual Energy Outlook 2010.

U.S. EIA. (2009b). Annual Energy Review 2009.

U.S. EPA. (2008). Inventory of U.S. Greenhouse Gas Emissions and Sinks: 1990-2006. Washington, DC: U.S. EPA.

Uno, K., & Kashiyama, K. (2008). Development of Simulation System for the Disaster Evacuation Based on Multi-Agent Model Using GIS. *Tsinghua Science & Technology, 13, Supplement 1*(0), 348-353. doi: 10.1016/s1007-0214(08)70173-1

US EPA. (2012). Cool Roofs Retrieved March 26, 2012, from http://www.epa.gov/heatisld/mitigation/coolroofs.htm

UW Milwukee. (2012). Great Lakes WATER Institute Green Roof Project: Green Roof Installation Retrieved March 26, 2012, 2012, from http://www.glwi.freshwater.uwm.edu/research/genomics/ecoli/greenroof/roofinstall.php#costs

van Breemen, A. J. N. (2001). *Agent-Based Multi-Controller Systems.* PhD, University of Twente, The Netherlands.

Van Dijk, D., & Spiekman, M. E. (2003). Monthly Method to Calculate Cooling Demand of EP Regulations *CEN/TC89 N870*. Brussels.

Van Dijk, D., Spiekman, M. E., & De Wilde, P. (2005, August 15-18). *A Monthly Method for Calculating Energy Performance in the Context of European Building Regulations.* Paper presented at the Building Simulation 2005, Proceedings of the Ninth International IBPSA Conference, Montreal, Canada.

Vytelingum, P., Voice, T. D., Ramchurn, S. D., Rogers, A., & Jennings, N. R. (2010). *Agent-based micro-storage management for the smart grid.* Paper presented at the 9th International Conference on Autonomous Agents and Multi-Agent Systems, Toronto, Canada.

Weidlich, A., & Veit, D. (2008). A Critical Survey of Agent-Based Wholesale Electricity Market Models. *Energy Economics, 30*(4), 1728-1759.

Wherry, R. J. (1931). A new formula for predicting the shrinkage of the coefficient of multiple correlation. *The Annals of Mathematical Statistics, 2*, 440-457.

Wilensky, U. (1999). NetLogo Retrieved March 26, 2012, from http://ccl.northwestern.edu/netlogo

Wittmann, T. (2007). *Agent-Based Models of Energy Investment Decisions*. Heidelberg, Germany: Physica-Verlag.

Wolak, F. A. (2000). An empirical analysis of the impact of hedge contracts on bidding behavior in a competitive electricity market. *International Economic Journal, 14*(2), 1-39.

Wolak, F. A., & Patrick, P. H. (1997). The Impact of Market Rules and Market Structure on the Price Determination Process in the England and Wales Electricity Market (Vol. POWER Working Paper PWP-047): Univ. California Energy Institute.

Wu, C. F. J., & Hamada, M. S. (2009). *Experiments: Planning, Analysis, and Optimization* (2nd ed.). New Jersey: Wiley.

Wulfinghoff, D. R. (2000). Measure 8.1 Reducing Cooling Load: Windows & Skylights *Energy Efficiency Manual*: Energy Institute Press.

XJ Technology. (2012). AnyLogic Retrieved March 26, 2012, from http://www.xjtek.com/

Yamaguchi, Y., Fujii, T., Morikawa, T., & Mizuno, M. (2004). Residential end-use energy simulation at city scale. *Building and Environment, 39*(8), 959-967.

Yamaguchi, Y., Shimod, Y., & Mizuno, M. (2007). Proposal of a modeling approach considering urban form for evaluation of city level energy management. *Energy and Buildings, 39*(2007), 580-592.

Zhang, J., Zabrowski, D., Schrock, D., Lane, M., Fisher, D., Athalye, R., . . . Liu, B. (2010). Technical Support Document: 50% Energy Savings for Quick-Service Restaurants. Richland, Washington: Pacific Northwest National Laboratory.

Zhang, Y., Augenbroe, G., & Vidakovic, B. (2005). *Uncertainty analysis in using Markov chain model to predict roof life cycle performance*. Paper presented at the 10 DBMC International Conference on Durability of Building Materials and Components, Lyon, France.

Zhao, F., Martinez-Moyano, I. J., & Augenbroe, G. (2011). *Agent-based modeling of commercial building stocks for policy support.* Paper presented at the the 12th International Building Performance Simulation Association Conference, Sydney, Australia.

Zhao, F., Wang, J., Koritarov, V., & Augenbroe, G. (2010a, September 27th-29th, 2010). *Agent-based Modeling of Interaction between Commercial Building Stocks and Power Grid.* Paper presented at the IEEE Conference on Innovative Technologies for an Efficient and Reliable Electricity Supply, Waltham, MA.

Zhao, F., Wang, J., Koritarov, V., & Augenbroe, G. (2010b, 27-29 Sept. 2010). *Agent-based modeling of interaction between commercial building stocks and power grid.* Paper presented at the Innovative Technologies for an Efficient and Reliable Electricity Supply (CITRES), 2010 IEEE Conference on, Waltham, USA.

Zhou, Z. (2010). *Agent-Based Simulation and Optimization with Learning and Applications on Electricity Markets.* PhD Dissertation, Rensselaer Polytechnic Institute, Troy, New York, USA.

Zhou, Z., Chan, W. K. V., & Chow, J. (2007). Agent-based simulation of electricity markets: a survey of tools. *Artificial Intelligence Review, 28*, 305-342.

Zhou, Z., Chan, W. K. V., Chow, J. H., & Kotsan, S. (2009). *Duopoly electricity markets with accurate and inaccurate market goals.* Paper presented at the Proceedings of the 2009 Winter Simulation Conference (WSC), Austin, TX, USA.

Zimmerman, R. D., Murillo-Sánchez, C. E., & Thomas, R. J. (2011). MATPOWER Steady-State Operations, Planning and Analysis Tools for Power Systems Research and Education. *IEEE Transactions on Power Systems, 26*(1), 12-19.